Open University of Catalonia

Doctoral Thesis

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# Applications of the Internet of Things and Optimization to Inventory and Distribution Management

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# *Abstract*

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**Applications of the Internet of Things and Optimization to Inventory and Distribution Management**

by David RABA

Livestock production in the European Union represents 40% of the overall agriculture output. The European feed sector is of utmost importance to the livestock industry. Farm animals in the EU-28 consume an estimated 478 million tons of feed a year, of which 163 million tons are produced by compound feed manufacturers (FEFAC, 2018). The European feed industry is a growing industry, with an estimated turnover at €50 billions, that directly employs approximately 110,000 people, most of them in rural areas where employment offers are usually scarce. Even though most of the compound feed plants are small and medium enterprises (SMEs), they have an average production volume of 40,000 tons of compound feed per plant (FEFAC, 2019). The quality of this compound feed is really important to farmers, because it directly correlates with milk or meat quality. A better knowledge of the farm's nutritional needs gives the feed manufacturer the best position to plan raw material procurement, as well as give them a reliable supply chain, with short lead times that will replenish their silos before they run out of feed. Final delivery is often done by trucks. Hence, an efficient distribution relies on how routes have been planned. The same truck will cover a wider product variety for the same trip, depending on the number of compartments. Moreover, this transport fleet can be totally or partially owned by the feed manufacturer. Outsourcing is commonly used to increase service capacity during peak periods. At the feed mill, raw materials are processed into grain or pellets. According to the demand, which varies throughout the week, a certain number of products should be produced and kept in stock. The more orders per day a feed manufacturer has, the more complex it is to achieve optimal production and distribution. For a make-to-order processes, it is of utmost importance to have a demand forecast, precisely to adopt certain make-to-stock process, thus smoothing the production peaks. As a result, being able to serve large orders and unexpected demands will depend on these decisions. This thesis elaborates on the research done towards the implementation of a computer-aided solution to address the problem of delivering animal feed to farms.

# *Acknowledgements*

I would like to thank my supervisors Dr. Angel A. Juan, Dr. Daniel Riera and Dr. Daniel Guimarans for all their help and advice with this PhD. I would also like to thank my start-up colleagues, without whom it would not have been possible, Salvador, Oriol, Uzair, Agustí, Tomi, Esteve and Jaume. I also appreciate all the support I received from the rest of IN3 team, Alejandro, Javi, Pedro, Rafael, Christopher and Lluna. I am also grateful with people from the distinct partners and clients I have had the opportunity to work with: Baywa, Dugdale, Primetics, Batalle, Terragrisa, SAVETO, Lantmännen and the top-secret UK based company. Lastly, I would like to thank the Spanish MINECO, the GENCAT for the studentships that allowed me to conduct this thesis and INSYLO for the opportunity to develop this work from its guts.

# Contents

# Chapter 1

# Introduction

If you can dream it, you can do it.
Always remember that this whole thing
was started with a dream and a mouse.

WALT DISNEY

## 1.1 Motivation

As the global human population grows and logistics improve, livestock production (pig meat, poultry, beef, cattle, etc.) is forecast to grow further. However, satisfying increasing and changing demands for animal-source foods requires a further shift from extensive to intensive-scale operations. This intensification means a progressive introduction of industrially manufactured compound feeds for the livestock sector. Commercial animal feed companies are best placed to provide such formulated feeds, but there is a strong pressure to optimize the use of resources while providing the lowest cost of production to the farmer. Compound feed production is a global growing industry with a one billion tones produced yearly worth of $400 billion. The EU28 is the third largest feed producer in the world (16% share), along with USA (17%) and China (18%). By 2030, feed production is predicted to double due to the increase mechanization and meat consumption in emerging economies (The Food and Agriculture Organization (FAO), 2019; Tilman, Balzer, Hill, and Befort, 2011).

The animal feed supply chain to farm, where feed suppliers and livestock farmers play an important collaborative role, suffer from great inefficiencies for both stakeholders. These are due to a very traditional and inefficient supply chain management, more precisely: a) Bad estimations of feedstocks by the farmer, b) Uncertainty of feed demand and c) Obsolete bin monitoring and restocking methods (Cutler, 2014). The compound feed industry is also competitive in that it works in a market which has essentially achieved maturity. Following the intensification trend, they have been progressively merged into large companies that perform under the integrated production system, where they aim to control the whole or partial process of animal-source food production. Although feed management is primarily the responsibility of the farmer, most of the big players (Cargill, Nutreco, ForFarmers, Vall Companys, El Pozo, ABagri, etc.) of this 'livestock intensification' are adopting precision feeding schemes from farrowing to fattening farms which can be a highly effective tool in enabling a reduction of feed intake per animal while also maximizing individual growth rates (The European Commission, 2018). It enables the provision of the right amount of feed, in the right nutrient composition, at the right time. However, main efforts to connect on-farm feeding activities with logistics of getting feed to farm have hitherto been unsuccessful due to the difficulties to accurately measure animal farm feed-stocks. Nowadays, big corporations are investing to narrow this gap as they recognize that it is essential to plan the logistics of feed movements from the feed mill to the farm site to protect the feed as much as possible as well as seek for increased efficiency for supply chain players, boosting business profitability.

## 1.2 Market research

A large part of the intensive livestock sector in Spain is organised using an integration model. The integrator, usually a large corporation in the food industry, is the owner of the animals and is responsible for most value chain activities such as manufacturing feed, veterinary services, animal slaughter or sale of the production. Farmers, usually on small farms, are limited to offering their facilities and workforce during the animal fattening process. This is the most prevalent model in 95% of poultry farms and 80% of pig farms in Spain. Another part of the sector is made up of large farms that produce their own feed and are totally self-sufficient. These companies also carry out many of the value chain activities and most end up sending the processed products to supermarkets. Finally, there is a small group of independent farms that are procured from a free feed market led by a few large manufacturers. This market structure (Figure 1.1) is expandable to the rest of Europe and the majority of the world's industrialised countries. In general, there is a tendency towards an integration model and replacing small farms with other larger farms with a high level of automation.

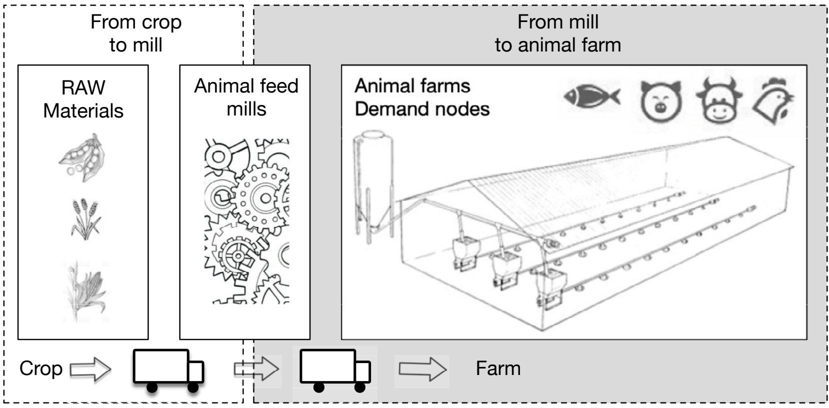



FIGURE 1.1: Animal-feed delivery supply chain from mill to farm.

Large food industry corporations directly or indirectly control the logistics of silo replenishment and have a direct interest in monitoring inventories of feed on farms. The ranking of the top 10 feed producers in Europe comprises: ForFarmers (NL), Nutreco (NL), De Heus (NL), DLG Group (DK), Agrifirm Feed (NL), Agravis Raiffeisen (DE), Avril/Glon Sanders (FR), Veronesi (IT), DTC Deutsche Tiernahrung (DE), Danish Agro Group (DK). In Spain the top 3 companies in the ranking are: Nanta, COVAP and Vall Companys. All of these companies control a park of more than $10,000$ silos each, with feed productions ranging from $1,500$ to $6,500$ tons per year and turnovers ranging from 350 million to 1.5 billion euros.

Given the data released by the FEFAC (European Feed Manufacturers Federation), in Europe there are about $4,000$ production units of compound feed with a turnover of 50 billion euros and a production of 156 million tonnes. Spain is ranked in second position amongst European countries with 13.59% of the production. Europe, in turn, is the 3$^{rd}$ world power after China, USA and the rest of Asia. Given the average capacity of a silo

(12 to 15 tones), the average frequency of replenishment (1 to 3 weeks), the average load percentage per replenishment (60%-75%) and an overcapacity rate (30%-50%), we can estimate an approximate number of $103,500$ silos in Spain and 1 million in Europe.

Hence, one may see how important are the *Compound Feed Suppliers* if we aim to improve the feed supply chain to farm. In Europe, there are more than $3,500$ companies whose main business is to produce and/or distribute feed for farm animals. They are a very good target due to the following reasons: First, the 47% of the European silos ($375,000$) are in hands of 50 feed suppliers who manage, on average, $7,500$ silos each. Hence, each target user of the Top 50 represents a huge business opportunity of EUR 2.85M plus a recurrent revenue of EUR $540,000$ per year (service fees and maintenance). Table 1.1 shows the top 10 *Compound Feed Suppliers* of the EU companies and two additional (13th and 18th EU rank), that are 2nd and 3rd within the Spanish ranking.

TABLE 1.1: Top 10 EU Compound Feed Manufacturers + TOP 3 ES

| Rank | Company | Country | kTn[1] | Silos |
|---|---|---|---|---|
| 1 | Nutreco | NL | 5,900 | 29,500 |
| 2 | DLG Group | DK | 4,500 | 22,500 |
| 3 | Veronesi | IT | 3,150 | 15,750 |
| 4 | AB Agri | UK | 2,227 | 11,135 |
| 5 | Triskalia | FR | 2,000 | 10,000 |
| 6 | Aveve Group | BE | 1,609 | 8,045 |
| 7 | Vall Companys Group | ES | 1,580 | 7,900 |
| 8 | Myronivsky Hliboproduct | UA | 1,564 | 7,820 |
| 9 | Amadori | IT | 1,500 | 7,500 |
| 10 | Cherkizovo Group | RU | 1,495 | 7,475 |
| 13 | Agropecuaria de Guissona | ES | 1,202 | 6,010 |
| 18 | Coren | ES | 857 | 4,285 |

[1] Source: www.feedstrategy.com

Feed production is a growing global industry with $1,000$ Mtn. produced yearly and a turnover of EUR $374,000$M. The EU28 is the third largest feed producer in the world (share of 16%), generating a turnover of EUR $50,000$ M [1]. All this compound feed is transported to farms, and stored into bins supplied into the barns by using feeding systems. A rough estimation of total installed feed bins/silos into farms, comprises globally $5M$ silos [2] ($800,000$ only in the EU28 [3] located in industrial livestock farms to store animal feed. By 2050, feed production and the number of silos is predicted to double [4] due to the increase mechanization and meat consumption in emerging economies.

[1] IFIF, Global Feed Production

[2] The number of silos in the EU has been calculated by means of the same estimation as the global amount of silos.

[3] Number obtained from the division of the global production of feed ($1,000$ Mtn.) by the average amount of feed that is stored in a silo in a year (200 tonnes)

[4] IFIF, The Global Feed Industry

TABLE 1.2: Top 10 EU Compound Feed Manufacturers

| Market | Mtn.[1] | % | Silos |
|---|---|---|---|
| EU | 160 | 16% | 800K |
| USA | 170 | 17% | 850K |
| CHINA | 190 | 19% | 950K |
| BRAZIL | 70 | 7% | 350K |
| Rest of the world | 410 | 41% | 2,05M |
| Total | 1,000 | 100% | 5M |

[1] Source: www.feedstrategy.com

## 1.3 Objectives and outline

This thesis work responds to a need arising throughout the whole EU, addressing EU28 challenges from two angles. On the one hand, the EU Directive 767/2009 ensures a high level of feed safety and animal health covering the traceability, prevention and control of feed contamination monitoring different control points. As the proposed solution provides the traceability of feed inventories and storage conditions (temperature and humidity) it helps to prevent feed contamination issues and analyse the possible causes when they happen, assuring the Directive accomplishment. On the other hand, since the Smart Logistics cloud platform allows the collaboration between feed suppliers and livestock farmers, optimizing the logistics involved in the delivery process, the carbon food print of the feed supply chain will be reduced. This ultimately contributes to the European's target of reducing by 60% GHG emissions from transport by 2050.

Therefore, the main objectives of the thesis are summarised as follows:

- **Optimize Transport Cost**; The reduction of the cost of transport for the procurement of animal feed to farms is obtained in 3 different ways: First, by reducing the number of trips made to each silo, secondly, increasing the truck's payload for each delivery shipment round, and finally reducing the distance traveled during each delivery shipment round. Through Optimisation of the silo's loading cycles, the required number of shipments of supplies can be reduced within year. However, currently the farmer launches replenishment orders when stock level is low and the ordered quantity is calculated based on an estimated level. In some cases of well integrated farms and feedstock suppliers, trucks visit farms on a weekly basis and fill silos according to predicted consumption and established delivery rounds. In none of the cases, the procurement cycles are the optimal. Optimised are both the points of order and load, resulting in smaller number of expeditions (a greater volume of cargo for each supply operation), reduced delivery shipment round sizes (the truck is loaded to its maximum permitted level and deliveries are grouped in such a way that the total distance is the smallest).
- **Mitigate Workplace Injuries**; the task of inspection of silos is eliminated completely together with the inherent risks of this activity.
- **Lowering Inventory Levels**; Implementation of a VMI where replenishment orders process is completed automatically. Human intervention will be limited, and in most cases all that the farmer will have to do is to press a button and complete approval

of a replenishment alert order pushed to their smart phone. VMI removes the need for the customer to have significant safety stock because the supplier manages the resupply lead times. Lower inventories for the customer can lead to significant cost savings, even lowering purchasing costs. In this area the labour savings will be 80%.

- **Improve Demand Forecast**; High growth in the animal feed market is aided by the growth strategies of major players in the form of expansions and investments, which also helps in enhancing the product portfolio and reaching out to new target markets. Furthermore, the growing livestock population along with the shift from unorganized livestock farming to the organized sector is further expected to propel the market growth opportunities in the coming years. However, the high price volatility of raw materials is expected to hinder the growth of the market during the forecast period. Also, a growing shift towards the adoption of a vegan-based diet is expected to impede the growth of the animal feed market in the forecast period and in the upcoming years. Demand forecast allows you to better anticipate future demand and properly plan both the supply of raw materials, and production, as well as the distribution.
- **Improve Traceability and Safety**; It is of utmost importance to ensure the appropriate storage conditions by measuring temperature and humidity conditions of storage of the feed in the silo. This information is useful for handlers of food security (usually the manufacturer of feed stock) to be able to predict risk and to determine the causes of contamination when it happens. In this sense, it may be difficult exactly quantify economic savings that may arise, but they can be very large when you consider that an untracked problem in the food chain can result in a European fine, that an uncontrolled feed stock contamination can lead to the destruction of an entire flock of animals, that negative public publicity can lead to reduced sales of certain animal stocks.

### 1.3.1 Industrial PhD

This thesis work has been develop within the research framework of an Industrial Doctorate Plan. The aim of the Industrial Doctorates Plan is to contribute to the competitiveness and internationalisation of Catalan industry, strengthen the tools for recruiting the talent generated in the country and place future PhD holders in the right place to carry out R&D&I projects in a company. The essential element of the industrial doctorate process is the research project carried out at a company or institution, where doctoral students will further develop their research training in collaboration with a university or research centre, and which is the object of a doctoral thesis. Therefore, the industrial doctorates act as a bridge for knowledge transfer and encourage closer ties between Catalan industry, universities and research centres.

In our case, this research project has been carried out within the company INSYLO Technologies SL. INSYLO (formely UBIKWA Systems SLU.) is a technology-based startup founded on 7$^{th}$ May 2013, located in the Science and Technology Park of the University of Girona. They are specialized in the field of the Internet of Things and their mission consist on developing an advanced sensing platform for future Smart Farming.

INSYLO currently has an office space of 90 m$^2$ equipped with the necessary fittings and IT systems for carrying out software and hardware research and development. In addition, it has a 45 m$^2$ workshop equipped with an electronics laboratory and the space and equipment necessary to start production operations and logistic distribution. The devices' components assembly, firmware loading, quality control, packaging and distribution will take place in the workshop; as well as any repairs of faulty devices required. These facilities are located at the University of Girona's Parc Científic i Tecnològic, and there is the opportunity to hire new modules as and when they are required. INSYLO has a competent and multidisciplinary team with professionals from different backgrounds capable of developing all INSYLO's key R&D and product development lines.

INSYLO has collaborated with the Internet Computing & Systems Optimization Group (DPCS-ICSO) from the Open University of Catalonia. This group embraces a wide skill profile set. From Internet-supported transportation in smart cities to Internet-based computing & collaboration, information- and technology-based (IT), systems around us are becoming more complex to manage due to their global scale, dynamic inter-dependencies, decentralized operations, real-time requirements, and high uncertainty levels. Academics in the Operations Research & Analytics (ORA) and Computer Science (CS) communities focus on developing interdisciplinary models, algorithms, and software solutions oriented to improve the performance and efficiency of these IT systems. In the context of the CYTED and Erasmus+ International Networks, the senior members of the DPCS-ICSO consolidated research group (2014-SGR-337) have been collaborating since 2009 with researchers from other universities and research centers around the world in the development of computational intelligence solutions that allow our industrial partners to significantly increase their efficiency and competitiveness levels. More precisely, the collaborative framework has been build around their research line of Systems Optimization in Transportation & Logistics that aims to developing intelligent algorithms and software solutions for supporting complex decision-making processes in transportation logistics, real-time positioning (outdoor, as well as indoor), and smart cities. In particular, simheuristic (Juan, Faulin, Grasman, Rabe, and Figueira, 2015) and learnheuristic (Calvet, Lopeman, Armas, Franco, and Juan, 2017) algorithms combine metaheuristic optimization, simulation, and machine-learning techniques to efficiently deal with uncertainty and dynamic issues in real-life systems.

## 1.4 Main research contributions

This document is based on research outcomes that are published in indexed journals and the proceedings of international peer-reviewed conferences. Relevant publications by the author of this thesis are highlighted at the beginning of each chapter and cited where necessary. The cover pages of the articles that serve as basis of this work can be found in appendix A. The main research outcomes that are published or currently in the review process of indexed journals are listed below. The discussions and results presented in this work are based on some research outputs in the form of publications in indexed journals and the proceedings of peer-reviewed international conferences. Developed research dissemination includes:

### 1.4.1 Publications

- Raba, D.; Estrada, A.; Panadero, J.; Juan, A. (2020): "A Reactive Simheuristic using Online Data for a Real-Life Inventory Routing Problem with Stochastic Demands". Int. Transactions in Operational Research, 27(6), 2785-2816 (indexed in ISI SCI, 2019 IF = 2.987, Q2; 2019 SJR = 1.018, Q1). ISSN: 0969-6016. https://doi.org/10.1111/itor.12776

  - **Abstract**

    In the context of a supply chain for the animal-feed industry, this paper focuses on optimizing replenishment strategies for silos in multiple farms. Assuming that a supply chain is essentially a value chain, our work aims at narrowing this chasm and putting analytics into practice by identifying and quantifying improvements on specific stages of an animal-feed supply chain. Motivated by a real-life case, the paper analyses a rich multi-period inventory routing problem with homogeneous fleet, stochastic demands, and maximum route length. After describing the problem and reviewing the related literature, we introduce a reactive heuristic, which is then extended into a biased-randomized simheuristic. Our reactive approach is validated and tested using a series of adapted instances to explore the gap between the solutions it provides and the ones generated by existing nonreactive approaches.

  - **Main contributions of PhD-student:**
    This work was completed in cooperation with Prof. Dr. Angel A. Juan and Dr.Javier Panadero from the Universitat Oberta de Catalunya in Barcelona, and Dr. Alejandro Estrada from of Universitat Rovira i Virgili in Tarragona. As a first author of this publication, the PhD-student was contributing to the review of relevant literature in the field, the design of the simulation-optimization algorithm, the analysis of obtained results, and the completion of the manuscript. Prof. Dr. Juan, Prof. Dr. Panadero and Dr. Estrada supported the article development with their expertise and guidance.

- Raba, D.; Juan, A.; Panadero, J.; Bayliss, C.; Estrada, A. (2019): "Combining Internet of Things with Simulation-Optimization in a Food Supply Chain". 2019 Winter Simulation Conference. Maryland, USA. December 8-11, p. 1894-1905, IEEE. https://doi.org/10.1109/WSC40007.2019.9004952

  - **Abstract**
    This paper discusses how the Internet of Things and simulation-based optimization methods can be effectively combined to enhance refilling strategies in an animal feed supply chain. Motivated by a real-life case study, the paper analyses a multi-period inventory routing problem with stochastic demands. After describing the problem and reviewing the related literature, a simulation-based optimization approach is introduced and tested via a series of computational experiments. Our approach combines biased-randomization techniques with a simheuristic framework to make use of data provided by smart sensor devices located at the top of each farm silo. From the analysis of results, some managerial insights are also derived and a new business model is proposed.

  - **Main contributions of PhD-student:**
    This work was completed in cooperation with Prof. Dr. Angel A. Juan, Dr.Javier Panadero and Dr. Christopher Bayliss from the Universitat Oberta de Catalunya in Barcelona. As a first author of this publication, the PhD-student was contributing to the review of relevant literature in the field, the analysis of obtained results, and the completion of the manuscript. Prof. Dr. Juan and Prof. Dr. Panadero supported the article development with their expertise and guidance. Dr. Bayliss contributed with the mathematical model presented to describe the problem solved.

- Raba, D.Tordecilla, R.; Copado, P.;Juan, A.; Mount, D. :"A Digital Twin for Decision Making on Livestock Feeding". INFORMS J. on Applied Analytics, Submited: 5th February 2021. Favourable review. Second review due 23-Jun-2021.

– **Abstract**

This work is part of the IoFEED project, which aims at monitoring approximately 325 farm bins and investigates business processes carried out between farmers and animal-food producers. We propose a computer-aided system to control and optimize the supply chain to deliver animal feed to livestock farms. Orders can be of multiple types of feed and shipped from multiple depots by using a fleet of heterogeneous vehicles with multiple compartments. Additionally, this case considers some business-specific constraints, such as product compatibility, facility accessibility restrictions, prioritized locations, or bio-security constraints. A digital-twin based approach is implemented at the farm level by installing sensors to remotely measure the inventories. Our approach combines biased-randomization techniques with a simheuristic framework to make use of data provided by the sensors. The analysis of results is based on these two real pilots and showcases the insights obtained during the IoFEED project. The results of this work show how the Internet of Things and simulation-based optimization methods combines successfully to optimize the feeding operations of livestock farms.

– **Main contributions of PhD-student:**

This work was completed in cooperation with Prof. Dr. Angel A. Juan and Dr. Pedro Copado and PhD candidate Rafael Tordecillas from the Universitat Oberta de Catalunya in Barcelona, and Mr. Daniel Mount from the company INSYLO. The article is currently in the review process (second review) of the cited INFORMS journal. As first author of this publication, the review of relevant literature in the field, the design of the simulation-optimization algorithm, data preparation, the analysis of obtained results, and the completion of the manuscript as well as leading the research effort. Moreover, the student was in direct contact with the Group Batalle company and the Dugdale company to obtain data and define the completed case-study. The PhD-student was contributing to gathering requirements and constraints from each partner. PhD student Rafael Tordecilla contributed with result analysis and was involved in all steps of the article completion. Dr. Pedro Copado implemented the final algorithm. Prof. Dr. Juan and Mr. Mount supported the article development with their expertise and guidance.

- Vila, O.; Boada, I.; Raba, D.; Farres, E. A Method to Compensate the Errors Caused by Temperature is Structured-light 3D Cameras. MDPI Sensors, 21, 2073. Accepted: 12th March 2021. https://doi.org/10.3390/s21062073

– **Abstract**

Although low cost red-green-blue-depth (RGB-D) cameras are factory calibrated, to meet the accuracy requirements needed in many industrial applications proper calibration strategies have to be applied. Generally, these strategies do not consider the effect of temperature on the camera measurements. The aim of this paper is to evaluate this effect considering a commodity camera. To analyze this camera performance, an experimental study in a thermal chamber has been carried out. From this experiment, it has been seen that produced errors can be modeled as an hyperbolic paraboloid function. To compensate for this error, a two-step method that first computes the error and then corrects it has been proposed. To compute the error two possible strategies are proposed, one based on the infrared distortion map and the other on the depth map. The proposed method has been tested in an experimental scenario with different cameras and also in a real environment. In both cases, its good performance has been demonstrated. In addition, the method has been compared with the Kinect v1 achieving similar results. Therefore, the proposed method corrects the error due to temperature, is simple, requires a low computational cost and might be applicable to other similar cameras.

– **Main contributions of PhD-student:**
This work was completed in cooperation with Prof. Dr. Imma Boada from the Universitat of Girona in Girona, the PhD candidate Oriol Vila and Dr. Esteve Farres from the company INSYLO. As third author of this publication, the PhD-student was contributing to the review of relevant literature in the field, the experimental design and the analysis of obtained results. PhD candidate Vila, performed the experiments, contributed actively to the resulting methodology and implemented agreed algorithms. Dr. Farres supported the article review. Dr. Boada supported the article development with their expertise and guidance.

### 1.4.2 Patents

- Gelada, J.; Farres, E.; Raba, D.; Haupt, M.; Gurt, S.: "A Method and a System for Assessing the Amount of Content Stored Within a Container". U.S. Patent No. 10,488,245. Washington, DC: U.S. Patent and Trademark Office, 2019.

  – **Abstract**
  Method and a system for assessing the amount of content stored within a container.The method comprising attaching a 3D sensor on a top part of the container in a position and with an orientation such that its field of view is oriented towards the content stored in the container; acquiring, by the 3D sensor, a depth map; and computing, by a computing unit, a 3D surface model by processing said acquired depth map and using said given position, orientation and field of view, and a 3D level model by removing from the computed 3D surface model the points corresponding to the interior walls of the container, using a 3D function that searches the intersection or matching between the 3D surface model and the shape of the container, and filling in the missing points corresponding to the content that falls out of the field of view of the 3D sensor.

  – **Main contributions of PhD-student:**
  This work was completed in cooperation with Mr. Jaume Gelada, Mr. Marc Haupt, Mr. Salvador Gurt, Dr. Esteve Farres from the company INSYLO. As co-author of the granted patent, the PhD-student contributed with the completion of the manuscripts needed to fulfill the patent request, as well as the amendments introduced into the claims finally protected by this patent. Claims proposed by the PhD-student where the ones finally accepted by the European agency.

### 1.4.3 Conferences & Workshops

- Raba, D: "INSYLO - Animal Feed Supply Chain Optimization". CYTED Workshop. Madrid, Spain. November 28-29, 2016 (oral).

- Raba, D: "INSYLO - Benefits from FIWARE Architecture for an IoT start-up". 1st FIWARE Summit, Malaga, Spain. December 13-15, 2016 (oral).
- Raba, D: "FIWARE Agrifood business case: INSYLO", IoT World Congress, Barcelona. Oct. 25th-27th, 2016 (oral).
- Raba, D: "INSYLO - FIWARE Architecture for an IoT start-up". 1st FIWARE Summit, Malaga, Spain. December 13-15, 2016 (oral)
- Raba, D; "Insylo: The IoT platform for the animal feed supply chain", Cube Tech Fair, Berlin 10th-12th May 2017 (poster)
- Raba, D: "Insylo: Smart Management of silos". 1st FIWARE Summit, Malaga, Spain. November 28th-29th, 2017 (oral)
- Raba,D.; Gruler, A.; Riera D.; Gelada, J.; Juan, A. (2017): "Combining real-time information with a variable neighborhood search metaheuristic for the inventory routing problem: a case study at UBIKWA systems". Presentation. 12th Metaheuristics International Conference (MIC). July 4-7, 2017.
- Juan Perez, J. Panadero, C. Bayliss, L. Martins, A. Freixes, D. Raba. Agile Optimization in Transportation and Logistics . XXXVIII Spanish Conference on Statistics and Operational Research. SEIO - Alcoi. September 3-6, 2019.
- Juan, A.; Faulin, J.; Raba, D.; Freixes, A.; Reyes, L. (2018): "Simheuristic Algorithms for Transportation and Logistics Problems under Uncertainty". Actas del XIII Congreso de Ingeniería del Transporte. Gijon, Spain. June 6-8, 2018.
- Juan, A.; Faulin, J.; Reyes, L.; Raba, D.; Freixes, A. (2018): "Simheuristics: Extending Metaheuristics to solve Optimization Problems under Uncertainty Scenarios". Abstracts del XXXVII Congreso Nacional de Estadística e Investigación Operativa. Oviedo, Spain. May 29 - June 1, 2019
- Raba,D., Gurt, S., Vila, O. and Farres, E., An Internet of Things (IoT) Solution to Optimise the Livestock Feed Supply Chain. International Conference on Cloud Computing and IOT (CCCIOT 2020). April 25 26, 2020, Copenhagen, Denmark.
- Raba, D.; Tordecilla, R. ; Mount, D. ; Riera, D. : "A Digital Twin for Decision Making on Livestock Feeding". Seminar on BigData and Decision Support Systems in Agriculture, 14-16 October 2020. Lleida, Spain. (oral - Best presentation award)
- Raba, D.; Tordecilla, R. ;Copado, P.; Mount, D. ; A. Juan, A. : "A Digital Twin for Decision Making on Livestock Feeding". 2020 Online Workshop SI-Transportation, 10-11 November 2020, Barcelona, Spain (oral)
- Masip, D.; Raba, D.: "Research carrier at UOC - Industrial Doctorate Experiences". 2020 1st Virtual Job Fair at Open University of Catalonia, 16-17 November 2020, Barcelona, Spain (Interview) URL: media, 00:25 onwards
- Raba, D.; Mount, D. : "IOFEED - Use Case 5.5 - Efficiency along the value chain". Future Farming Final Event, 16-18 May 2021. Wageningen, The Netherlands (Online presentation).
- Raba, D.; Mount, D. : "IOFEED - Use Case 5.5 - Feed supply management". Future Farming Final Event, 16-18 May 2021. Wageningen, The Netherlands (Online presentation).

### 1.4.4 Awards, grants and research projects

Along with the academic publications, during this PhD work, INSYLO has secured several grants and awards due to the innovativeness and high technological level of their solutions. Key achievements related to this PhD work are:

- **IOFEED Project (2019-2020)**: A subprogram within the project Internet of Food & Farm 2020 (IoF2020) that explores the potential of IoT-technologies for the European food and farming industry. This collaborative project is funded by the

European Comission by the agreement No. 731884 with EUR 493.6K (use case 2282300206-UC005).

- **Industrial Doctorate MINECO (2016-2020)**: Predoctoral research grant from the Spanish Ministry of Economy and Competitiveness (DI-15-08176), basically covered company expenditures.
- **AGAUR Industrial Doctorate AGAUR (2016-2020)**: Predoctoral research grant from the the Catalan Agency for Management of University and Research Grants (2016-DI-038), mainly covered University expenses and courses.
- **Llavor 2018**: Seed funding to supporting academic initiatives to develop product or business ideas. Awarded through a Catalan grant, co-financed by the European Union through the European Regional Development Fund ERDF (AGAUR-FEDER, reference 2018 LLAV 00017).

## 1.5 Dissertation outline

This thesis is structured in the following blocks (Figure 1.2): Motivation and problem definition (Chapter 2), Value proposition (Chapter 3), Materials and Methods (Chapter 4), Application to a real case scenario (Chapter 5) and conclusions, future research, and contributions (Chapter 6).

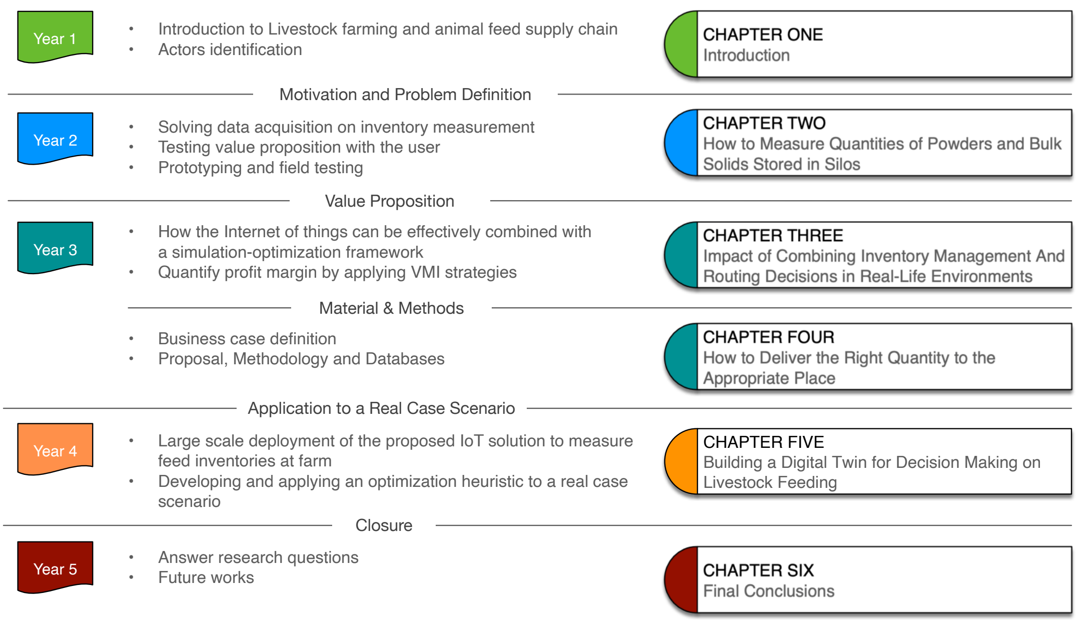



FIGURE 1.2: Thesis road map.

The first block focuses on the existing methodology employed to manage the animal feed supply chain to livestock farms. In particular, Chapter 2 introduces root problem of managing and measuring inventories of bulk solids stored into farm bins, describing their context, reviewing the main technologies used, and presenting a new methodology and physical sensor. Chapter 3 is devoted to validate the Value proposition, i.e., the integration of real-time inventories into metaheuristics-based frameworks to deal with Stochastic Combinatorial Optimization Problems (SCOPs). Chapter 4 provides a brief definition of addressed Vehicle Routing Problem (VRP). Afterwards, Chapter 5 presents a real world application of the proposed system to build the digital twin that integrates Internet of things and the optimization heuristics proposed in this thesis. The last block draws some conclusions, and identifies potential lines of future work in Chapter 6, while lists the publications, and presentations in contributions may be found at appendix A. Additional appendix sections have been also included to provide a deeper description of certain aspects like the research environment originated from the H2020 funded project IOFEED (Appendix B), a description of the process used to model the feeding curves used to forecast product and feed quantities in appendix C, and overview of the IoT system in appendix D. Finally in the appendix a report on the environmental analysis impact of the solution is also provided in appendix E.

# Chapter 2

# Measuring Livestock Feed Inventories

I have not failed. I've just found 10,000 ways that won't work.

THOMAS A. EDISON

## 2.1 Introduction

Being the farm's feed-stock one of the key asset to manage, the need for measuring this stored inventory in a reliable and accurate way becomes crucial to build any decision tool on top. There are several kinds of approaches in the market that have attempted to provide a solution to remotely monitor feedstocks in livestock farms bins. They either measure bin's weight or measure the feed level inside the bin. The availability of this remote monitoring systems will enable the use of smarter feed logistics platforms (SFLP). With gathered real-time feedstock data, and production data of both stakeholders (farmers & suppliers) taken mainly from suppliers' Information Management Systems (IMS). The SFLP would work in three areas: a) Feed demand forecast to predict the feed demand and the future stock levels in the farms, based on current stock levels and production data shared by farmers, b) Automatic restocking process that automatically would generate the restocking orders based on the selected restocking policies. Farmers would receive alerts and would be able to confirm the restocking orders with a simple click, and c) Feed suppliers can take full responsibility of the feedstocks (Vendor Managed Inventory, VMI) and process the restocking orders automatically, taking into account current stock levels, feed demand forecast, production data, and cost functions defined by the supplier. The SFLP will provide a solution to mitigate the uncertainty of demand, help smooth the peaks of production allowing smaller inventory buffers and reduce transport costs optimizing the shipping routes. SFLP will allow the feed plant to improve several business processes such as feed orders processing, ingredient purchasing, feed production, product storage, and delivery schedules. Research on collaborative supply chain strategies constitutes promising concepts in the establishment of sustainable freight transportation systems (Attaran and Attaran, 2007). Even though, the literature on this specific vertical (the well known VMI applied to livestock feed to farm) is really scarce. There is an interesting work, CHAINFEED (Hunt, Browne, and Higgins, 2003), where the authors introduced this new strategy for the feed producers to improve their supply chain performance. After modelling statistically the feed supply chain and simulating distinct replenishment scenarios, they highlighted the importance of having updated stock information to reduce model's uncertainty.

This chapter presents a new bin measurement system and supporting data processing methods to better estimate the volume and weight of stored compound feed in livestock farms. Additionally, this chapter aims to set the basis to optimize the animal feed supply chain for feed mills and farmers by developing a feedstock remote monitoring system, validate different business processes, as well as the scalability of the hardware solution.

## 2.2 Materials and Methods

The main approach and most direct way to measure weight is done by using the so called "load cells", which are installed in the bin's support structure. The second approach (level) uses level sensors usually based on cable, radar, ultrasonic or guided wave technology. Additionally, there exist similar products to our proposal present on the market (e.g., 3DLevelScanner Non-Contact Sensor by BinMaster in Christensen, 2019). These sensors make use of a complex radar system to measure a 3D feed surface as our proposal. Even though these sensors are completely out of scope for our environment due to: a) their high cost, what makes large deployments not affordable and b) the physical principle they rely on, that do not allow them to provide accurate and reliable data in small bins like the ones our environment present (fibber manufactured bins with a cylinder diameter of up to 3 meters). To access the data remotely, they often use standard data loggers and GPRS modems with private protocols. Measuring stock level within the bin is difficult since the feed surface is uneven (the difference between the lowest and the highest points can easily reach 2 meters). Since level sensors only measure the distance between the device and a single point in the feed's surface, measures have a lack of accuracy (Carson, 2000). The only solution in the market able to provide accurate measures (error below 1% relative to full capacity) are the load cells. However, their installation costs are extremely high (€$3,000$/bin including installation) for the market niche this work targets. Moreover, devices with the lowest price – ultrasonic and guided wave radars – cost per bin €$1,200$ plus €$150$ to €$300$ for annual maintenance and communication services. In addition, the functionality obtained by suppliers' standard software is limited to a daily record of the levels in the bins. If the customer requires a higher level of integration (which is the most common situation, since a single feed supplier manages several farms), the customization will raise even more the final price. With regards sensor network deployment and operations scalability, most of the solutions which are already in the market must be mains powered, raises the installation costs. Additionally, some farms have electricity generators which are only active for certain hours per week, failing to supply all day-round power to the devices and making them non-operable most of the time. Besides, the smart services offered by these devices do not go beyond checking the bin's feed level from the online platform and receiving an alert if they are low. They do not combine and analyse the data gathered from different devices, so they cannot forecast the feed demand and optimize inventories, production batches, delivery routes and raw materials purchases. Most of these devices suffer of the same pain, uncertain profitability, that avoids them to obtain a successful market uptake. Of course, several sensors are present in the literature that try to address similar problems in the smart city environment like the waste collection (Chandra, Sravanthi, Prasanthi, and R, 2019; Mamun, Hannan, and Hussain, 2014; Folianto, Low, and Yeow, 2015). Even though, none of them reach the required accuracy to measure bulk solids stored into farm bins.

### 2.2.1 Remote Monitoring System

The key enabling technology consists of a camera with a commodity RGB-D sensor that captures colour images along with dense pixel-wise depth information in real-time. With an embedded computer vision algorithm, it provides much more accuracy (error $< 3\%$) than traditional single-point level sensors (error $= 15 - 20\%$). Instead of using a single point measure like lasers or ultrasound, a matrix of $320x240$ readings over the feed's surface is taken. This device has been designed for providing up to 24 readings per day. It is battery powered with an integrated solar panel for recharging the battery pack. Each device mounts with a GSM module (4G/3G/2G) that allows the use of the cellular network when available. Electronics, batteries and energy harvesting have been configured to lower the energy consumption an enable a live-span of one month without solar contribution.

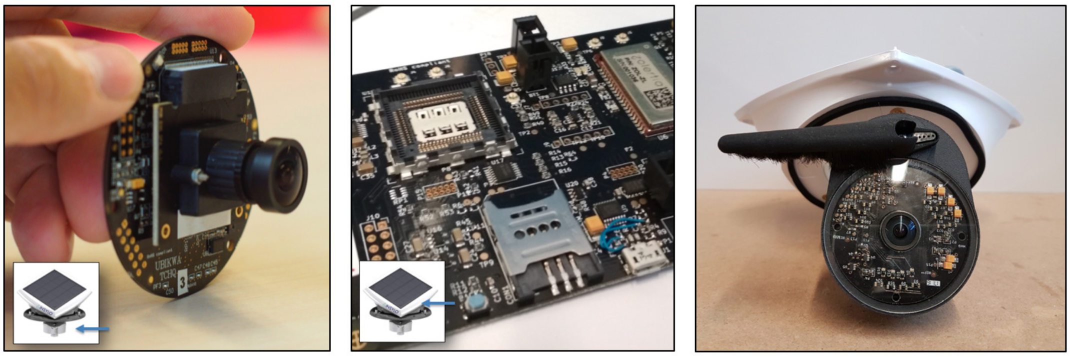


FIGURE 2.1: From left to right, the 3D sensor, communication electronics, and self-cleaning system.

This device does not require any cleaning or maintenance after installation since batteries must not be substituted and it has a self-cleaning system against dust and condensation (Figure 2.1). It has been designed to provide an easy installation. Figure 2.2 shows (1-4) how in four steps the sensor is placed by drilling a hole in the top cone, attaching an adapter ring and screwing the sensor, and (5-6) how the gathered RGB image and distances map looks like. In case a sensor has to be removed, a metal cap is also provided.

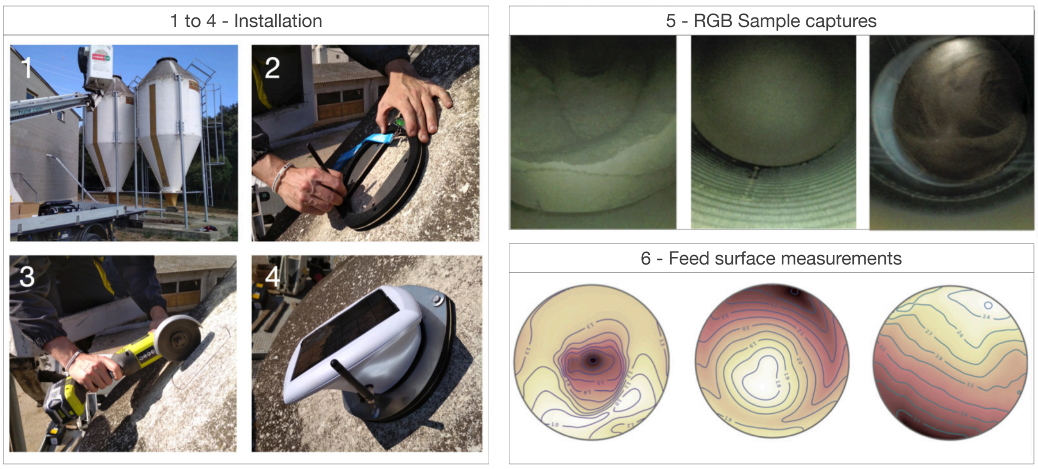



FIGURE 2.2: Four steps of the sensor installation procedure with (1) cherry picker placement, (2) hole marking and (3) drilling, (4) adapter ring placement and sensor fixation. Sample RGB images captured (5) and its corresponding distance maps (6) from camera.

As it is shown in Figure 2.3, the sensor measures distance from the camera (placed in the top of the bin) to the feed surface. Using this depth map ($320x240$ distances), the sensor: *(i)* performs a 3D reconstruction of the feed surface; *(ii)* intersects this surface with the user-defined bin geometry; and *(iii)* estimates the remaining volume. In the following subsection, the data processing applied from depth map to volume estimation is described.

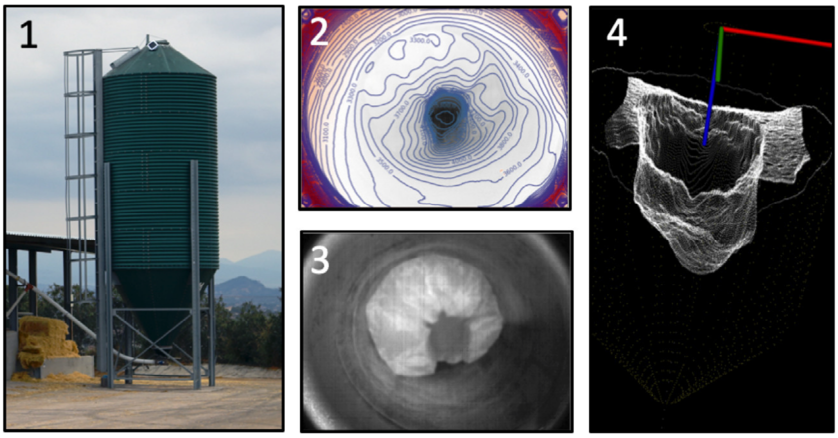



FIGURE 2.3: Illustrative example of feed bin (a), single shoot measured disparity maps (b top) and IR channel (b bottom) and feed surface reconstruction in distinct time steps (c-f) while feed is consumed.

The FIWARE IoT stack has been used as an Open Initiative for this project (Krčo, Pokrić, and Carrez, 2014) to develop cloud systems. FIWARE architecture has been demonstrated as a powerful and reliable solution for the implementation of IoT based applications. One of the key aspects of this architecture is the adoption of the OMA NGSI Context Management standard to manage and exchange context information about context Entities (Ramparany, Marquez, Soriano, and Elsaleh, 2014). In that sense, the Orion Context Broker has been used to model data. The Orion Context Broker is an implementation of the Publish/Subscribe Context Broker Generic Enabler. It decouples the consumers of data, like end users and M2M applications, from the devices, objects and resources that produce the data. The Context Broker provides an API that implements the NGSI-9 and NGSI-10 Context APIs (Bauer, Kovacs, Schülke, Ito, Criminisi, Goix, and Valla, 2010). It enables the interoperability of the systems with other use cases of the IOF2020 programme.

Figure 2.4 organises the knowledge of our problem. Distinct actors are contributing to the system. Apart from the Farmer and the Feed manufacturer, also technical experts are informing the system with data related to the specific feed diets delivered to farms. After data gathering, raw data is sent to the cloud systems to be processed.

### From Depth Map to Volume

Although the process applied to convert the raw depth map into the scalar volume has been designed specifically for our data pipeline, it is commonly known in the literature (Khoshelham and Elberink, 2012; Rosin, Lai, Shao, and Liu, 2019). A free-space approach is applied to estimate the bin's current stock. Hence, this free-space based method allows calculating the remaining empty volume of a bin by using the measured depth map from the inner bin and the measured or informed bin diameter. It is important to point out that the described method supports the free placement of the sensor on any top cone position. Hence, if the camera is not centred and perpendicular to the surface, it is required to geometrically transform the inferred inner surface. The geometric transformation values can be introduced manually given the camera pose and location or automatically extracted using the bin walls (if they are presents in the depth map).

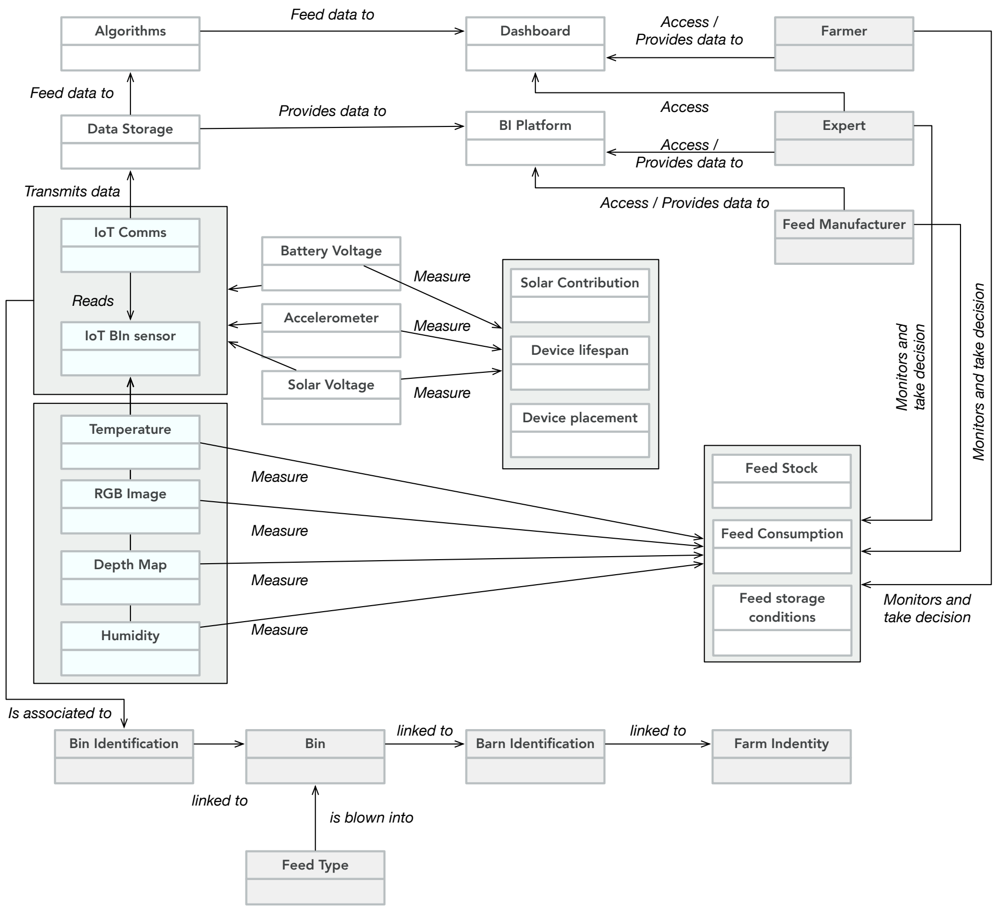



FIGURE 2.4: Domain model for the livestock feed remote monitoring system.

Figure 2.5 shows the pipeline applied to estimate remaining volume for each bin. First, the point cloud generation (step 1), in this phase we translate each single pixel value from the depth map to a real-world coordinate using the calibration matrix. Next step implies geometrically transform the obtained mesh to get it aligned with the origin of coordinates (step 2), in our case, the central axis of the bin at its maximum high. Bin walls are removed from 3D mesh by filtering via face normal filtering (step 3). This procedure enables us to effectively remove points that do not belong to the feed surface. Afterwards, the point cloud is decimated by removing outliers within a predefined neighbourhood in a fixed radius. A quality check is performed to assess how reliable is the information available (step 4). A threshold (TH) is set experimentally, to decide including previously capture depth maps into the current measurement to fill the gaps by overlapping two or more historical depth maps. We also exclude the points that do not belong to the theoretical geometry of the bin. The surface sampling rate is quantified by comparing the theoretical maximum bin area that can be measured and the relative area described by each depth map. Hence, only feed surface points score to this ratio. The remaining surface is approximated by a combination of multi quadratic radial basis functions (RBF) as explained in Carr, Beatson, Cherrie, Mitchell, Fright, McCallum, and Evans, 2001. RBF allows us to create a clean and smooth point grid (step 5) to recover missing zones produced by sunlight, temperature or other external factors as will be discussed on Section 2.3. Finally, the interpolated surface is triangulated using the Delaunay algorithm (Cheng, Dey, and Shewchuk, 2012) on the projected points in the $x, y$ plane (step 6). Then the surface of each triangle is multiplied by its mean depth ($z$) value to obtain the total empty volume. We infer the

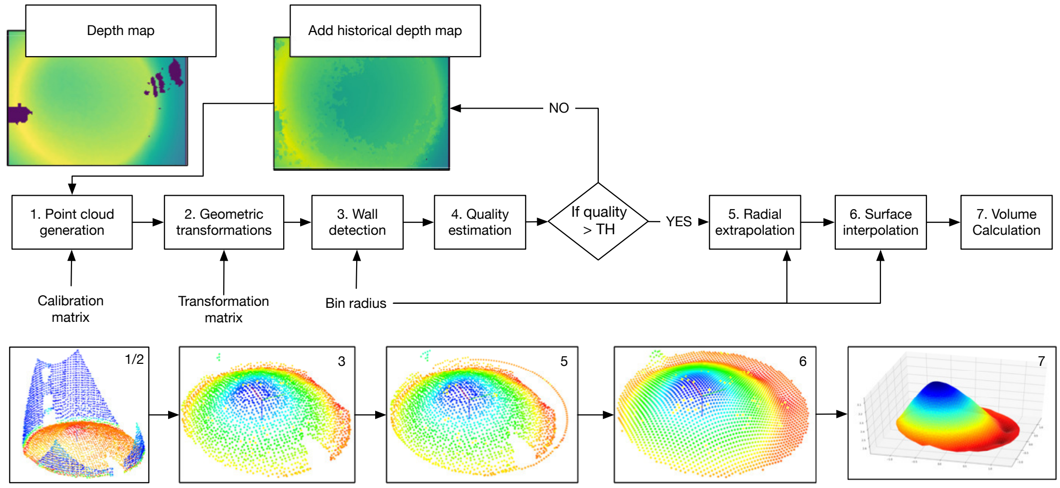



FIGURE 2.5: Flow chart of procedure used to determine the volume.

remaining volume by subtracting the calculated empty volume to the total bin volume (step 7). All this pipeline is currently executed on our cloud systems. Even though, each device performs an image acquisition process to ensure data quality before sending raw depth map and RGB images to the cloud.

#### Measure of a Known Weight

One of the main drawbacks of measuring inner volume to estimate the weight is the assumption that the bulk density of the stored product remains constant throughout the entire bin. This might be true for smaller bins but in modern commercial-size bins, bulk density of feed compounds substantially increases due to compressive and hoop stresses (Haque, 2013). In our experiments feed density is modelled as a constant value, but an additional packing factor is considered. While the objective of this research was to determine the field pack factors and bin capacities for on-farm and commercial bins used to store corn in the U.S. (Bhadra, Casada, Turner, Montross, Thompson, McNeill, Maghirang, and Boac, 2018), we manually adjust packing factor for every bin based on a known feed load and the provided density by the feed manufacturer. Hence, our weight estimation is calculated by multiplying the remaining volume estimation and the given density.

Figure 2.6 shows a suggested process to integrate feed densities. Feed mill is most likely actor to be capable of informing densities, while the Farmer or facility responsible has the final confirmation of the inventory location at farm (which silo has been refilled with a certain recipe). Although the weight time series from the sensors may allow us to identify loads, manual confirmation is needed to identify where the order has been placed. Hence, a pseudo-automated pipeline may be applied to enrich weight series with density changes.

### 2.2.2 Planning the Feed Delivery

As it has been briefly explained in Chapter 1, feed market is divided into two main segments. First, there is a *free market*, where farmers are free to buy to any feed supplier and buying decisions based on best price and service, and second, there is another *captive market* that operates in a highly integrated model where farmers and feed suppliers are owned by the same agribusiness corporate or where farmers have long term contracts with feed suppliers. From the feed manufacturer perspective, one of the main pains is the uncertain demand

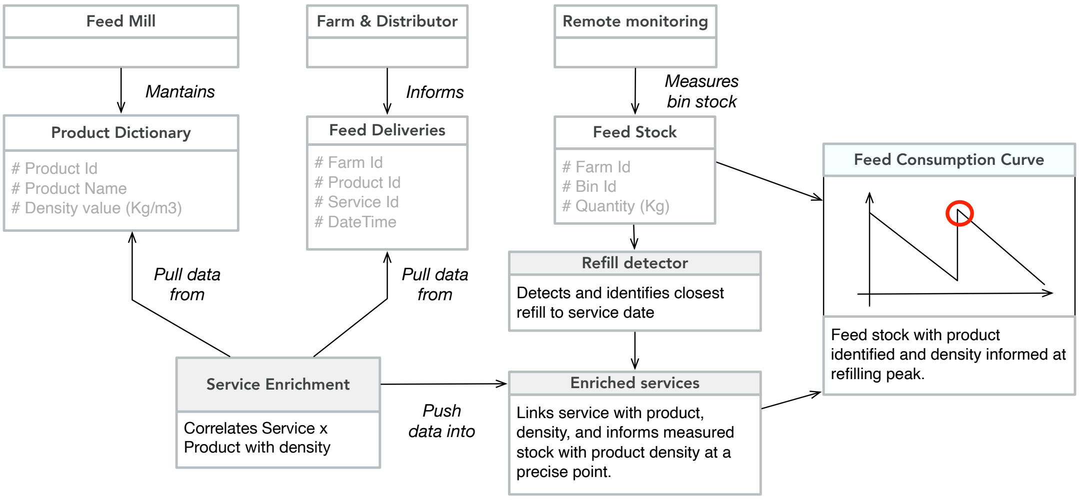



FIGURE 2.6: Product density integration.

forecast. *Captive market* is normally more predictable, but it is still highly depended on observed production plan done by the farmer to generate new feed orders. On *free market*, the need for an accurate demand forecast is a must. Modelling the feed consumption is one of the most wanted tools a demand planner could ask for, because a) it would be really appreciated to have a projection of feed intake and b) it enables them to detect abnormal patterns on animal feed consumption.

Feed efficiency (FE) is an important production trait as feed accounts for 60–70% of the costs for layer production systems (Willems, Miller, and Wood, 2013). Although we cannot measure the feed conversion ratio (FCR) efficiency between individual animals, an initial estimation to be measured is the daily consumption rate (DCR) for a given bin. There are two main sources of information. First, the feedstock measured by using remote monitoring sensors and second, fattening schemes designed by livestock managers. This work focuses on the first source of information to estimate DCR from hourly measured stocks. Algorithm 1 explains the procedure followed to compute DCR by using two or three days of hourly based estimations.

This algorithm to compute DCR and the remaining days of stock estimation (ETA) makes use of $W$, a date ascent ordered time series with estimated weights including the last available reading where $|W| \geq 48$. It samples a period of three days since the current time; $minLoad$ as the minimum load detected in Kg. Any increase in weight below this value is filtered; $order$ that defines the order of the used low-pass filter used; $f_{cut}$ as its cutoff frequency in Hz; and $w_{current}$ as the current stock in Kg.

## 2.3 Results

### 2.3.1 Remote Monitoring System

In order to validate the sensor's accuracy, some reference bins have been upgraded with weighting cells. Hence, for those bins, the real weight is collected along with the new sensor-based estimation.

**Input:**

$W$, $minLoad$, $order$, $f_{cut}$, $w_{current}$

**Output:**

$DCR$, $ETA$

*Preserve peaks from being filtered* :

Compute differences $W_{diff} \leftarrow |W_{i+1} - W_i|$

Get the peaks $W_{peaks} \leftarrow W_{diff} \geq minLoad$

Remove the peaks $W_{nopeaks} \leftarrow W - W_{peaks}$

*Apply a Lowpass Butterworth filter (LBF)*:

$W_f \leftarrow LBF(W_{nopeaks}, order, f_{cut})$

*Group $W_f$ by date* :

$W_{agg}(date) \leftarrow max(W_f(date))$

Compute DCR value $DCR \leftarrow Average(W_{agg})$

*Compute ETA value* :

$ETA \leftarrow Average(W_{agg})\ w_{current}$

**return** $DCR$, $ETA$

**Algorithm 1:** Using weight timeseries to compute Daily Consumption Rate (DCR) and estimate remaining days of stock (ETA)

### Test Benchmark

We have installed in our facilities a double silo system with feeders that allow us to transport bulk solids between both silos. In practice, this setup has become our reference standard for measuring improvements with INSYLO devices.

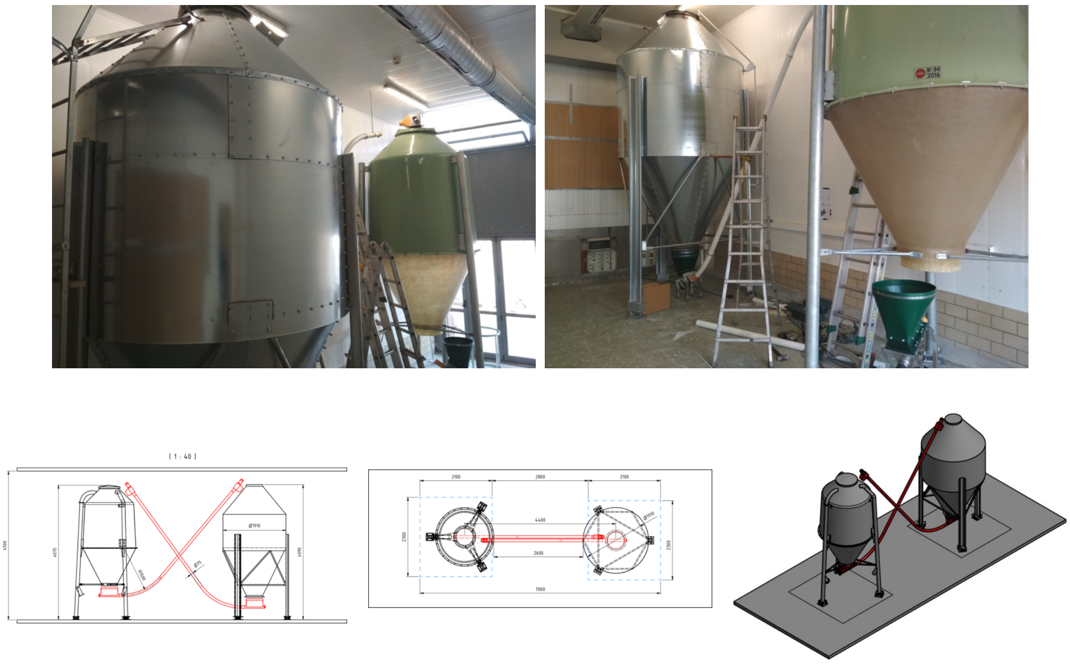


FIGURE 2.7: Test lab bulk solid storage.

We have seen in some pilots, where floury feed is used, the creation of uneven surfaces and chimneys, which are not detected by low resolution sensor. As a resulting of this behavior, consumption is not correctly measured until the structure collapse and changes the sampled surface. We have stored floury feed to ensure working on the worst scenario and correctly reproduce such.

### Accuracy and Repeatably

A bin has been placed on a weighting bay to validate the accuracy and repeatability of our sensor. Having installed a device on this bin, we proceed to fill the bin with materials until its maximum capacity ($TotalCapacity$). A discharging process is carried out while measuring. The sensor has been configured to work in continuous mode. Hence, the device is connected to the main power to be capable of sending data every 15 minutes. This test has been done with the collaboration of an independent company. They have provided us a bin as well as materials used to perform the tests on their facilities. This test has been repeated for five times. An external team have been operating on the bin and collecting information about the whole process of draining the bin. We have collected the amount of Kg that they removed from the bin and also the remaining material ($W_{ref}$). Data is collected and processed during the discharge operation to estimate the remaining stock ($W_{est}$). Figure 2.8 shows data collected from the five runs performed and relative error (Eq. 2.1) obtained compared with the reference weight given by load cells.

$$e_{rel} = \frac{|W_{ref} - W_{est}|}{TotalCapacity} \tag{2.1}$$

Overall, results shows an average deviation between our estimations and the weighing system used is about $1.15\%$ with a maximum deviation of $4.15\%$ in one of the points. It is important to point out that, when materials are very close to the sensor (sensor measures distances from 60 cm to 8.5 m) it is observed that sensor has some inaccuracies, data provided on this point is an estimation based on the maximum bin capacity. It is planed to add a short range sensor to overcome this drawback. This reality is observed on initial measurement with full bin for every run. We do not take into account error introduced in this extreme range where estimated error may exceed $6\%$ of the bin's maximum capacity. So far, only four bins are tested in field conditions, where load cells and our sensor have been installed for each bin. Results achieved are similar to the ones observed in laboratory conditions. It is important to notice that load cells typically have impressive worst-case specifications, and their actual performance is usually better than the specification. As a general rule, they operate with a $0.01\%$ percent of span, which is really accurate. Meanwhile, other single-point-based sensors (ultrasound, laser, contact sensors, etc.) highly depend on how uneven is the feed surface.

### Reliability

Considering this sensor aims to work on outdoor conditions, an important point to validate consists of verifying that the depth measurement is stable to environmental conditions. electronic sensors, signal conditioning circuits are sensitive to temperature, that often causes output drifts on range measurements regardless of the used technology. Reflective surfaces also affect RGB-D cameras, but considering the analyses done by other works (Giancola, Valenti, and Sala, 2018), it can be deduced that the color and the material of a target influence the depth measurement. The reflectivity of the surface indicates the quantity of light that bounces back to the sensor, as well as external light sources add noise to the camera. Even though surface reflectivity, sunlight, temperature affect the available signal-to-noise ratio on captured images by reducing the depth map quality.

We have defined a *Quality Index* (Eq. 2.2 where $0 \leq Qi \leq 1$), to rank acquired depth maps according to the results obtained. In other words, how far a measured depth map ($D$) is from the perfect acquisition, being 1 the perfect depth map, and 0 not having

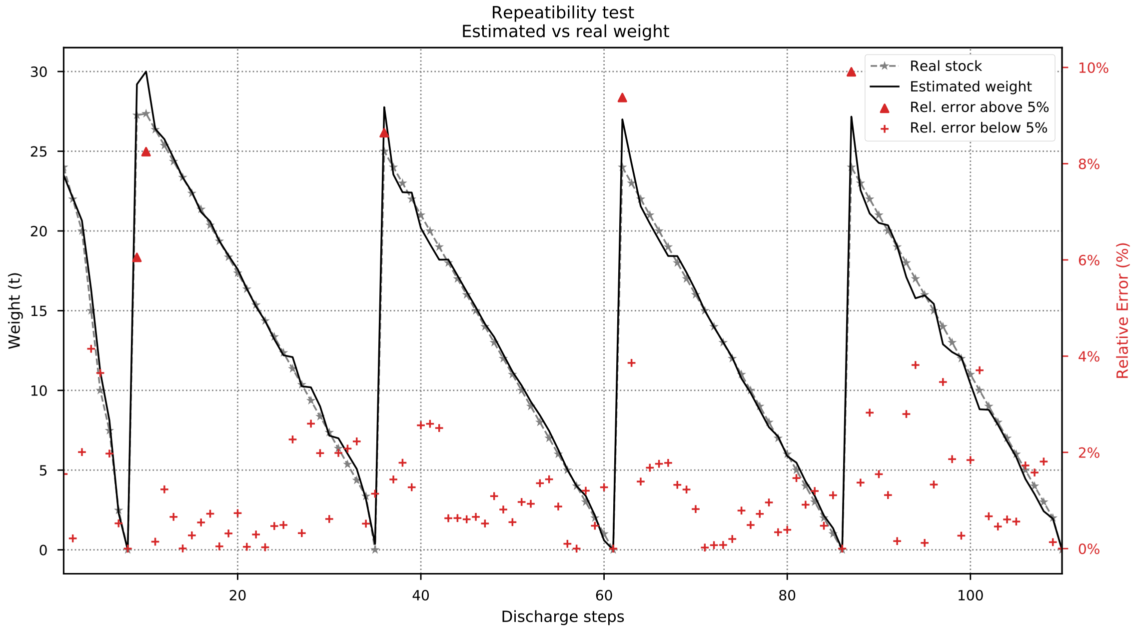



FIGURE 2.8: Weight estimations compared with weight reference (load cell) for the five runs with relative error to $TotalCapacity$.

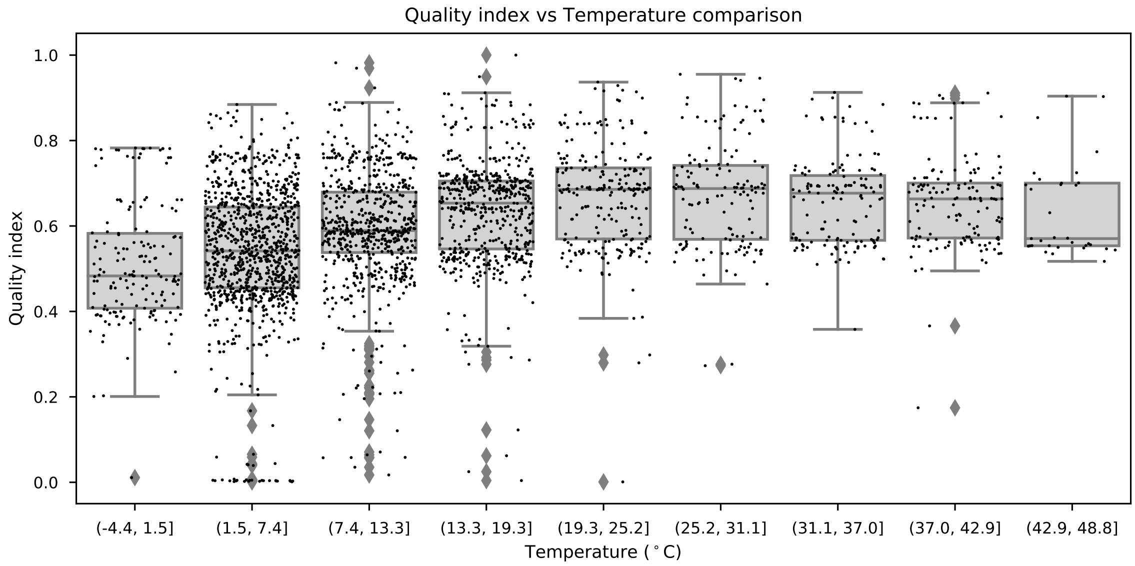



FIGURE 2.9: Two months of readings from 6 random bins: Quality Index vs temperature at acquisition time.

available any data point. Eq. 2.3 defines $f(D,x,y)$ that determines if a depth reading is available or not.

$$Q_i(D,n,m) = \frac{\sum_{n=0}^{N}\sum_{m=0}^{M} f(D,n,m)}{n*m} \tag{2.2}$$

$$f(D,x,y) = \begin{cases} 1, & \text{if } D[x,y] \geq 1 \\ 0, & \text{otherwise} \end{cases} \tag{2.3}$$

Figure 2.9 shows how *Quality Index* varies with temperature measured by our sensor. It shows a decline in *Quality Index* below 10 °C. Most of this temperature effect has been corrected by setting up an appropriate warm-up time to the device and reached accuracy level is not affected.

#### Limitations

The system has been designed to work under appropriate conditions, but it is with limitations. Some preventive actions has been taken to ensure these conditions: First, a cleaning system has been included (essentially a wiper) to maximise the likelihood to have a clean reading, removing hooked feed. Even though, dust suspended in the air in the headspace between the sensor and the feed surface reduces the depth map quality or even a blind reading when bins were measured shortly after or while filling. The sensor should be able to measure the entire bin wall/feed surface interface. Sometimes, when bins are very full and the surcharge cone of grain exceeded the eave height of the bin, or simply the system's field of view is obstructed, our estimation algorithm takes some assumptions and extrapolate readings to fill the gaps. This may lead us to introduce some error in our estimations.

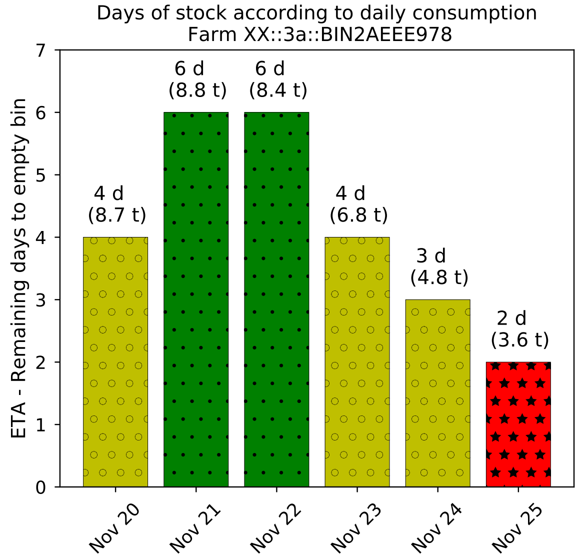
### 2.3.2 Planning the Feed Delivery

Regarding to DCR and ETA estimations, filter parameters have been set for the experiments with $f_{cut} \leftarrow 2/24$ and $order \leftarrow 4$. Figure 2.10 gives an example of daily stock, daily consumption rate (DCR) and ETA values for every day. Detailed reading of Figure 2.10 shows how ETA estimation may vary between subsequent days. Although inventory does not decrease, ETA value uses a time-window, so daily consumption varies while current date moves forward. Hence, ETA value may increase by decreasing the average consumption estimated within the time-window used.

This is the main information provided to farmers along with other gathered data (ie. temperature, humidity and visual image of the inner bin, etc.). Additionally to BP1 benefits, BP2 aims on changing the business strategy moving the workload balance of maintaining the feedstock to the feed supplier, so they can handle and manage the correct and exact amount of feed for each bin that covers their client needs (the farmer) while, at the same time, optimising the supply and logistics chain costs (production, own stocks, product shipping/distribution, etc.). Figure 2.11 depicts the global information available to feed manufacturers to plan according to feed types, consumption rates, and simple demand forecast (ETA).

### 2.3.3 Technology Adoption

After several improvements on algorithmic and electronic design, a set of 50 devices are installed across farms to validate device accuracy, durability and weather conditions resilience. Since the installation done across distinct farms, they have been collecting data for a working period of 10 months. We have assessed a good functionality of the sensor, not only in terms of data accuracy and repeatability but in terms of usability and deployability. It takes 20 minutes to install and configure in a bin without ladder, lesser if truck mounted crane is not needed (ladder availability). Apart from the observed limitations (Section 2.3.1), it is interesting to point out that during these pilots we have experienced some implementation barriers with farmers. They typically focus mainly on their core business and have little or no interest in data gathering. Moreover, it is required a reliable technological basis to encourage farmers into low-risk implementations, even in the




| | Nov 20 | Nov 21 | Nov 22 | Nov 23 | Nov 24 | Nov 25 | Avg. |
|---|---|---|---|---|---|---|---|
| Kg/day | 1,377 | 1,377 | 1,377 | 1,875 | 1,282 | 1,083 | 1,395 |

FIGURE 2.10: Sample location, remaining stock estimation based on daily consumption. Coloring is based on a traffic light schema where color gets red when stock live-span reaches two days of stock.

scenarios where they are not the facility owners. Although it is commonly accepted that smart farming requires information sharing across supply chains, farmers are still and often not willing to provide access to their data in the light of uncertainties about ownership and security of their data. While these concerns tend to dilute when they are not the real owners of the facility, it will be required the implementation of policies to give farmers ownership of their data. All the actors of the value chain seek for proven results of direct impact and improvement potential on individual farm and supply chain levels.

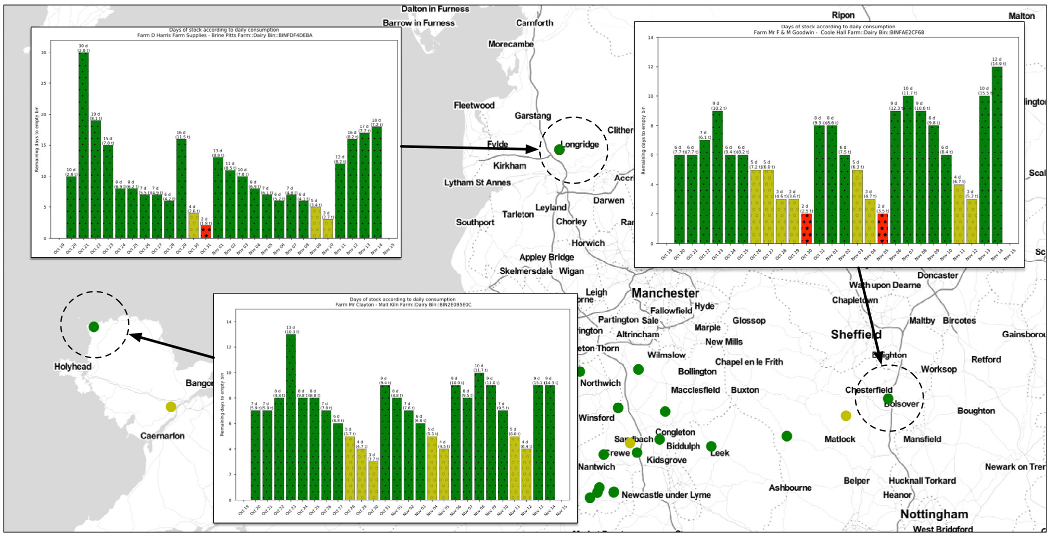



FIGURE 2.11: Case study UK1 pilot with 20 locations and 27 sensor mounted bins.

## 2.4 Conclusions

A new monitoring system for animal feed storage bins that gives volume estimations with errors below 5% in most of the cases has been presented (see Section 2.3.1 to check limitations). According to the results obtained, the average deviation between our estimations and the used weighing system can achieve up to 1.15% relative full scale error. This system is designed to enable large deployments. It is battery powered with solar charging. Its installation is done in lesser that 20 minutes each bin without maintenance required. Additionally, a data processing pipeline is presented to generate business insights to help decision takers, either farmers or feed manufacturers. The main problem of this work aims to address originates from a practical application of feed compounder delivery to animal farms, where the main objective is to satisfy all the farm demands at a minimal cost. In the same vein, this work enables a closed-loop system where periodical measures gathered from the field will be used by heuristics to dynamically optimise inventories and routes. Thus, this updated information from real inventories will reduce the uncertainty with which heuristics has to deal.

Next Chapter elaborates on how reducing the uncertainty on inventory levels positively affects the multi-period inventory routing problem (IRP) we aim to address in our application field.

# Chapter 3

# Inventory Management and Routing Decisions

You make different colors by combining those colors that already exist.

HERBIE HANCOCK

## 3.1 Introduction

Livestock consume approximately 477 M tonnes of feed each year in the EU (Kleter, McFarland, Bach, Bernabucci, Bikker, Busani, Kok, Kostov, Nadal, Pla, et al., 2018). From this, 154 M tonnes of compound feed –typically preserved and stored in silos to supplement their own feed– were produced by the EU in 2015 (mainly for cattle, pigs, and poultry, respectively) to supplement their own feed. In the EU28 there are more than 800,000 silos on industrial livestock farms used to store compound feed according to animal production and consumption (FEFAC, 2016). For farmers, the feeding process at the farm has evolved from one of trial-and-error to precision planning. Since feed accounts for a large portion of the final cost of animal production, growers have to deal with specific feeding programs to maximize the feed profitability. Thus, in the case of pork, feed accounts for between 50% and 70% of the total cost of production (Rocadembosch, Amador, Bernaus, Font, and Fraile, 2016). This specific feeding programs lead them to scheduling precise feed deliveries with appropriate formulas. Being service level understood as the probability that no shortages occur between the time we order more feed stock and the time it arrives to the silo, setting service level targets is pure guesswork without inventory optimization. In feed manufacturing, distribution, and replenishment planning, the benefits of good demand forecasting include the capability of reducing feed stocks, minimize wrong or excessive orders, diminish urgent orders, reduce the safety stock and, in general, the uncertainty in the supply chain. Furthermore, it allows feed manufacturers to secure availability of raw materials and operate with lower capacities, service times, and production buffers. For these reasons, as increased feed prices have had biggest impact on animal growers and feed manufacturers margins, there is a clear ongoing need for the investment in how animal feed distribution to farms is managed. In this context, the current study adds to a literature that is scarce with respect to the impact of combining inventory management and routing decisions in real-life environments (Coelho, Cordeau, and Laporte, 2013).

In this Chapter, we propose a constructive heuristic for the multi-period inventory routing problem (IRP). This heuristic allows for establishing good refill policies for each customer-period combination, i.e., those individual refill policies that minimize the total expected cost over the periods. This cost is the aggregation of both expected inventory and routing costs. Our heuristic, which also uses biased-randomized techniques (Grasas, Juan, Faulin, De Armas, and Ramalhinho, 2017; Estrada-Moreno, Ferrer, Juan, Bagirov, and Panadero, 2019; Estrada-Moreno, Fikar, Juan, and Hirsch, 2019; Estrada-Moreno, Savelsbergh, Juan, and Panadero, 2019), is then extended into a simheuristic algorithm (Juan, Kelton, Currie, and Faulin, 2018), which allows to consider the inventory changes between periods generated by the random demands. Notice that the specific values of these random demands in one period might have a significant effect on the quantities to be delivered in the next period. Therefore, they might also impact on the associated routing plans. In addition, we also modify the former strategy by using online data on the real demands as it becomes available. This allows us to update the refill strategy at each period, thus generating a reactive algorithm. A range of computational experiments are carried out in order to evaluate the potential benefits of our simulation-optimization approach for the discovery of insights that can then influence decisions and drive changes to the process of animal feed distribution to farms.

This Chapter is structured as follows: Section 3.1.1 describes a typical agri-food supply chain; Section 3.2 provides a literature review, while from Section 3.3 to Section 3.4 it is formally described the problem addressed and presents our solution approach; Section 3.5 presents the computational experiments carried out and the obtained results; we also include a discussion in Section 3.6 with insights that would help to influence current business strategies; finally, the conclusions drawn from this study and identified lines for further research are summarized in Section 3.7.

### 3.1.1 Overview of the Agri-food Supply Chain

The agricultural industry is a typical application area of innovative supply chain management concepts such as vendor managed inventories (VMI), which are based on the collaboration among different actors in the value chain. VMI represents a trade-off solution for suppliers and producers, where cost reduction benefits both, with savings obtained from distribution and production costs due to an accurate demand forecast, along with effortless inventory management for the customer. Supplier has to decide then *when*, *how much*, and *how* to serve a client, typically based on agreed policies. The most used policies in practice are the *order-up-to-full-capacity* policy —where the quantity delivered to the customer is that to fill its inventory capacity— or the *order-to-a-maximum-level* policy —where supplier decides to deliver a specific amount to reach a given percentage of the holding capacity. Success of VMI implementation requires sharing demand and inventory status information with their feed suppliers, so that suppliers can take over the inventory control and purchasing function from the farmers. There are two drawbacks of VMI: *(i)* traditional fattening farms are reluctant and / or skeptical about sharing production plans with feed producers; and *(ii)* it requires the solving of the associated IRP, which is a *NP-hard* combinatorial optimization problem (Coelho, Cordeau, and Laporte, 2013).

The number of works dealing with the animal-feed business is scarce. In Hunt, Browne, and Higgins, 2003, a business analysis was performed, with the purpose of understanding and identifying the distinct actors involved in a supply chain. The work also discusses new strategies from the business point of view. The whole supply chain was modeled and simulated to illustrate VMI as a new business model. Although manufacturing and retail companies are used to VMI practices, most companies from the agri-food sector have not even began to experiment with this concept. The main barriers that have stopped its adoption come from the business model itself. While in countries like Spain the supply chain is owned and controlled by large companies, other countries use a free-market schema —where a variety of actors are involved. The former are clearly aware of VMI benefits, and try to optimize the full value chain. In free-market environments, where feed manufacturers could be involved in a more competitive market with other players, more aggressive strategies are needed to enroll key players with innovative VMI strategies.

An example of an agri-food supply chain can be seen in Figure 3.1. A central depot delivers animal feed to a set of farms, which are responsible for the feeding of their livestock. Traditionally, the supply process is based on two separated decisions. Each farm places replenishment orders according to their feed stock levels, which has a direct influence on the routing plan designed by the central supplier. This process is inefficient due to several reasons. On the one hand, routing plans by the supplier are highly dependent on the orders placed by the farms. On the other hand, current inventory levels within animal-feed silos are often manually measured through a time-intensive procedure shaped by highly-inaccurate demand estimates.

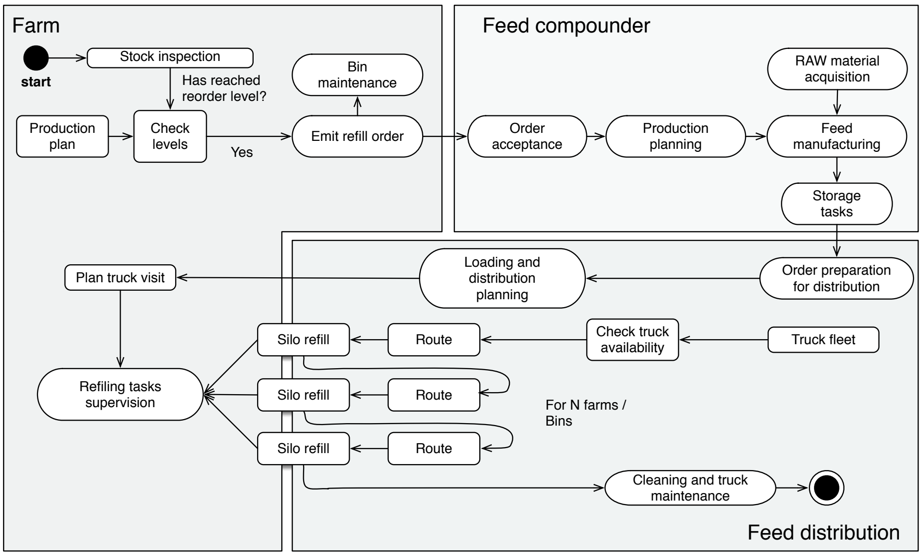



FIGURE 3.1: Activity diagram of an animal-feed delivery supply chain.

Typically, each farmer requires a different composition of feed, which means that the feed supplier must prepare the feed *ad-hoc* for each specific farm and deliver it in a short period of 24 to 48 hours. The timely delivery of animal-feed products to customers requires a high degree of coordination between customers, feed producers, suppliers, and transporters. Considering that each feed supplier delivers to several farms, the manufacturing and delivering process of animal feed is a key activity to be optimized. A feed supply chain can be divided into several main stages: feed production, processing, feed mill, farm, and transport & storage. In this context, the VMI concept can reduce overall supply chain costs. However, the lack of reliable and cost-effective solutions to remotely monitoring feed stocks on the farms forces farmers to manually assess stocks every week and send the refilling orders mostly by phone calls. This situation generates important inefficiencies all along the feed supply chain. First of all, inaccurate estimates of feed stocks by farmers, which causes: *(i)* farmers to run out of feed, forcing costly urgent orders that disrupt the production cycle of feed suppliers; *(ii)* the silo being fuller than expected, so trucks cannot unload the feed into the silo; and *(iii)* the silo being emptier than expected, forcing more trips than necessary and preventing the optimal use of the trucks load capacity. Secondly, uncertainty of feed demand, which lead them to: *(i)* a limited capacity on the feed suppliers side to foresee coming orders, which forces them to produce on-demand in a short period of 24 to 48 hours; *(ii)* that feed production cycles and delivery routes cannot be optimized based on cost criteria; and *(iii)* that purchases of raw materials cannot be optimized based on feed demand and market-price fluctuations.

## 3.2 Literature Review

This section reviews recent works on the inventory routing problem. Since the problem is *NP-hard*, our review focuses on the use of heuristic-based approaches, both for the deterministic and the stochastic versions of the problem. Andersson, Hoff, Christiansen, Hasle, and Løkketangen (2010) and Coelho, Cordeau, and Laporte (2013) present two extensive reviews on solving techniques and IRP settings. To correctly place this works among the vast literature available on the IRP, it is important to notice that the problem setting tackled in this paper establishes inventory and routing plans over multiple time periods in a one-to-many supply chain setting. While the works of Bertazzi, Bosco, Guerriero, and Laganà, 2013 and Solyalı, Cordeau, and Laporte, 2012 adopt order-up-to-level inventory strategies –which define a global refill stock level for all distribution centers–, this work discusses the maximum-level strategy as originally considered in Juan, Faulin, Caceres-Cruz, Barrios, and Martinez, 2014 on his single-period IRP –which defines an individual inventory plan at each client for every time period. Moreover, the possibility of product stock-outs at the end of each period is considered as proposed in Gruler, Panadero, Armas, Pérez, and Juan, 2018. This differs from other works such as the ones by Bertazzi, Bosco, Guerriero, and Laganà, 2013 or Solyalı, Cordeau, and Laporte, 2012, which introduced the backlogging concept. Although our work considers the customer demands to be of stochastic nature, it differs from these distinct sources since it introduces the dynamic IRP scenario were customers' demands are gradually revealed over time and decisions should be taken under limited foresight. Some metaheuristic approaches for deterministic and stochastic IRP variants are discussed in more detail in the following.

### 3.2.1 Related Work on the Deterministic IRP

Logistics an supply chain management is a challenging area and IRP is a key enabler for succeed on reaching optimal effectiveness on delivery and inventory processes. IRP has been studied using both exact and approximated methods. Heuristic algorithms are commonly used at early works like Abdelmaguid, Dessouky, and Ordóñez, 2009 for the finite multi-period IRP with backlogging. Later proposals applied a distinct metaheuristics, such as tabu search in Liu and Lee, 2011, Li, Chen, Sivakumar, and Wu, 2014, or Archetti, Bertazzi, Hertz, and Speranza, 2012. An adaptive large neighborhood search metaheuristic was developed by Aksen, Kaya, Salman, and Tüncel, 2014, while Popović, Vidović, and Radivojević, 2012 developed a variable neighborhood search (VNS) algorithm for a multi-product, multi-period IRP in fuel delivery with homogeneous multi-compartment vehicles. Popović, Vidović, and Radivojević, 2012 and Mjirda, Jarboui, Macedo, Hanafi, and Mladenović, 2014 also employed VNS-based approaches. Recent works combine metaheuristics with exact methods (matheuristics). Thus, for example, Cordeau, Laganà, Musmanno, and Vocaturo, 2015 combine a rich mixed-integer linear programming model with a constructive heuristic. Genetic algorithms have been also employed by Moin, Salhi, and Aziz, 2011 or Park, Yoo, and Park, 2016 to solve the multi-period IRP. Other population-based methods were presented in Shaabani and Kamalabadi, 2016.

Nambirajan, Mendoza, Pazhani, Narendran, and Ganesh, 2016 also extended the classical IRP formulation. A closer supply chain collaboration is considered by including replenishment activities at a central depot and different warehouses in a three-echelon supply chain. First, the replenishment policy of a set of manufacturers to a single depot is defined. Then, the routing of the central depot to multiple warehouses is planned by using a three stage heuristic based on clustering, allocation, and routing. An iterated local search algorithm for the cyclic IRP over an infinite planning horizon is discussed by Vansteenwegen and Mateo, 2014. Other heuristics and metaheuristics for the cyclic IRP have also been presented by Chitsaz, Divsalar, and Vansteenwegen, 2016, Raa and Dullaert, 2017, and Zachariadis, Tarantilis, and Kiranoudis, 2009.

### 3.2.2 Related Work on the Stochastic IRP

While the deterministic version has been intensively studied, the IRP under uncertainty scenario has been less analyzed so far. Some of the contributions address the problem of random demands by using incremental approaches to improve the cost (Jaillet, Bard, Huang, and Dror, 2002). Markov decision processes are commonly used to deal with this stochastic behaviour as done by Kleywegt, Nori, and Savelsbergh, 2004 or Hvattum, Løkketangen, and Laporte, 2009. The latter work models random demands by using discrete distributions, assuming an initial scenario tree, initially solved with a greedy randomized adaptive search procedure. Dynamic programming models also belong to the commonly used toolbox for modelling stochastic demands as in Bertazzi, Bosco, Guerriero, and Laganà, 2013, as well as mixed-integer linear programming formulations as in Solyalı, Cordeau, and Laporte, 2012. It is important to point out that these two works discuss on slightly different problems than the one addressed in this paper. They consider order-up-to level inventory strategies where the customer is filled up to its maximum capacity each time is visited. They also assume uniform random demands. Our approach, however, specifically explores distinct refilling strategies that minimize the total costs and offer distinct probability distributions to model customers' demands. Other works like Huang and Lin, 2010 have employed ant colony optimization to deal with uncertainty on a multi-product IRP. Li, Wang, and Chan, 2016 pay special attention to produce robust solutions. They also deal with IRP policies on stochastic customers' demands and replenishment lead-times. Roldán, Basagoiti, and Coelho, 2016 contribute to the dynamic and stochastic IRP problem. Yu, Chu, Chen, and Chu, 2012 introduce service level constraints to their stochastic IRP formulation. Environmental concerns are considered in Soysal, Bloemhof-Ruwaard, Haijema, and Vorst, 2015, jointly with demand uncertainty, estimating $CO_2$ emissions while planning the routes. A fuzzy probabilistic approach is proposed by Niakan and Rahimi, 2015, dealing with the minimization of $CO_2$ emissions in an IRP involving medical distribution. Rahim, Zhong, Aghezzaf, and Aouam, 2014 reduce the multi-period IRP problem from a stochastic stationary demand into a deterministic equivalent approximation model. Chen and Lin, 2009 introduce risk aversion concepts into their stochastic IRP solution. Juan, Faulin, Caceres-Cruz, Barrios, and Martinez, 2014 propose a hybrid simulation-optimization approach, combining a multi-start metaheuristic with Monte Carlo simulation to address the single-period IRP with stochastic demands. An enhanced algorithm for the single-period IPR with stochastic demands is discussed in Gruler, Panadero, Armas, Pérez, and Juan, 2018. Finally, Gruler, Panadero, Armas, Pérez, and Juan, 2020 provide a new heuristic-based algorithm for the multi-period IRP with stochastic demands. Our work extends the latter by incorporating a reactive concept which makes use of online data as it becomes available for the decision maker. We also adapt our method so it can be applied in a realistic environment regarding an agri-food supply chain.

### 3.2.3 Related Work on Simheuristic Algorithms

As described by Figueira and Almada-Lobo, 2014, simulation-optimization methods allow to hybridize both approaches in order to cope with: *(i)* optimization problems with stochastic components; and *(ii)* simulation models with optimization requirements. Extensive reviews and tutorials on simulation-optimization can be found in Fu, Glover, and April, 2005, Chau, Fu, Qu, and Ryzhov, 2014, and Jian and Henderson, 2015. Likewise, Andradóttir, 2006 provides a discussion on how random search can be integrated in simulation-optimization approaches. In this context, we are specially interested in the combination of simulation with metaheuristic algorithms, as initially proposed by Glover, Kelly, and Laguna, 1996; Glover, Kelly, and Laguna, 1999 and April, Glover, Kelly, and Laguna, 2003. Typically, these 'simheuristic' algorithms integrate simulation methods inside a metaheuristic optimization framework to deal with large-scale and *NP-hard* stochastic optimization problems. Hybridization of simulation techniques with metaheuristics allows us to consider stochastic variables in the objective function of the optimization problem, as well as probabilistic constraints in its mathematical formulation (Fu, 2002). As discussed in Juan, Faulin, Grasman, Rabe, and Figueira, 2015, the simulation component deals with the uncertainty in the model and provides feedback to the metaheuristic component in order to guide the search in a more efficient way. When dealing with stochastic optimization problems, performance statistics other than expected values could be considered as well. Hence, while in deterministic optimization one can focus on finding a solution that minimizes cost or maximizes profits, a stochastic version of the problem might require the analysis of other statistics, such as its variance, different percentile values, or its reliability level –i.e., the probability that a planned solution can be executed without disruptions. The simulation component can provide all these statistics, thus allowing for the introduction of risk-analysis criteria during the assessment of 'elite' solutions. Simheuristics have been employed in different application fields:

- *Transportation*: Juan, Faulín, Jorba, Riera, Masip, and Barrios, 2011 and Juan, Faulin, Jorba, Caceres, and Marquès, 2013 propose simheuristic algorithms for solving the single-period vehicle routing problem with stochastic demands; a similar approach is used by Gonzalez-Martin, Juan, Riera, Elizondo, and Ramos, 2018 to deal with the stochastic arc routing problem; Guimarans, Dominguez, Panadero, and Juan, 2018 analyze the two-dimensional loading vehicle routing problem with stochastic travel times, and proposes a simheuristic for dealing with it; also, Reyes-Rubiano, Ferone, Juan, and Faulin, 2019 study the routing of electric vehicles with limited driving ranges and stochastic travel times.
- *Production*: Juan, Barrios, Vallada, Riera, and Jorba, 2014 discuss the permutation flow-shop scheduling problem when processing times are stochastic, and propose a simheuristic algorithm and the use of survival analysis concepts to deal with it; Gonzalez-Neira, Ferone, Hatami, and Juan, 2017 introduces a simheuristic for the distributed assembly permutation flow-shop problem with stochastic processing times; likewise, Hatami, Calvet, Fernández-Viagas, Framiñán, and Juan, 2018 make use of a similar approach to set up starting times in a stochastic version of the parallel flow-shop problem.
- *Logistics*: Juan, Faulin, Caceres-Cruz, Barrios, and Martinez, 2014 and Gruler, Panadero, Armas, Pérez, and Juan, 2018 present simheuristic algorithms for solving inventory routing problems with stochastic demands; Armas, Juan, Marquès, and Pedroso, 2017 propose a simheuristic algorithm for the uncapacitated facility location problem with stochastic costs; in a similar way, Onggo, Panadero, Corlu, and Juan, 2019 use simheuristics to study agri-food supply chains with stochastic demands.

- *Computer Networks*: Cabrera, Juan, Lazaro, Marques, and Proskurnia, 2014 combine discrete-event simulation with a heuristic to enhance the allocation of computing resources in distributed networks over the Internet.
- *Smart Cities*: Gruler, Fikar, Juan, Hirsch, and Contreras-Bolton, 2017 and Gruler, Quintero-Araújo, Calvet, and Juan, 2017 analyze the waste collection problem in modern urban areas and propose a simheuristic algorithm to solve its stochastic variant.
- *Finance*: Panadero, Doering, Kizys, Juan, and Fito, 2020 consider a project portfolio optimization problem under uncertainty conditions, and employ a simheuristic to support decision making in this context.
- *Methodology*: Grasas, Juan, and Lourenço, 2016 and Ferone, Gruler, Festa, and Juan, 2019 extend two popular metaheuristic frameworks into simheuristic ones, so they can also deal with stochastic optimization problems in a natural way.

## 3.3 A Formal Description of the Deterministic Problem

Let $V = \{0, 1, \ldots, n\}$ denote a finite set of locations consisting of the depot (node $0$) and $n$ demand nodes. The set of demand nodes will be denoted by $V^* = V \setminus \{0\}$. With the goal of minimizing the total cost, the periodic IRP combines inventory and routing decisions over a finite planning horizon $P$ with $|P| > 1$ periods. We know in advance the customers' aggregated demand $d_{pi}$ at each demand node $i \in V^*$ during a period $p \in P$. Likewise, it will be assumed that the customers' aggregated demand at each demand node and period will always be satisfied. Thus, should a stock-out occur during a period $p$ at demand node $i$, an additional shipment from the depot to $i$ will be placed by the end of period $p$ to cover the non-satisfied demand –the cost of this extra shipment will be accounted as stock-out cost.

Regarding inventory management, the decision variables refer to the replenishment policies a farm can choose. Any policy selected for a node $i$ refers to a part of the maximum storage capacity that we decided to maintain in the silo for a given period $p$. Given the number of replenishment policies $m$, we consider that replenishment policies of node $i$ are equidistant values ranging from $0$ to $l_i^+$, where $l_i^+ > 0$ denotes the maximum storage capacity of $i$. Therefore, the replenishment policies $r_{il}$ of $i$ is equal to $\frac{l-1}{m-1} l_i^+$, for $l \in \{1, 2, \ldots, m\}$. For instance, if we choose $m = 5$, the replenishment policies for a given node $i$, will be $\{0, 0.25 l_i^+, 0.5 l_i^+, 0.75 l_i^+, l_i^+\}$. On the other hand, every demand node $i$ has initial stock available $l_{pi}^0$ during period $p$, and consequently, $0 \leq l_{pi}^0 \leq l_i^+$. The initial stock level for the first period $(p = 1)$ is given as an input. By the end of each period, the initial stock level for the next period can be computed as $l_{(p+1)i}^0 = \max\{r_i^p - d_{pi}, 0\}$, where $r_i^p$ is the replenishment policy chosen in the period $p$. Likewise, at this point the holding- or stock-out inventory cost at demand node $i$ and period $p$ can be obtained by using Equation (3.1), where $\lambda$ represents the unitary cost of holding surplus inventory by the end of a period, and $c_{0i}$ represents the cost of a direct shipment from the depot to demand node $i$ (this value is doubled in order to account for the return trip to the depot):

$$f\left(r_i^p, d_{pi}\right) = \begin{cases} \lambda(r_i^p - d_{pi}) & \text{if surplus } r_i^p \geq d_{pi} \\ 2c_{0i} & \text{if stock-out } r_i^p < d_{pi} \end{cases} \tag{3.1}$$

For each period $p$, a Capacitated Vehicle Routing Problem (CVRP) needs to be solved for those demand nodes $i$ with $r_i^p - l_{pi}^0 > 0$, i.e, for those nodes whose quantity of product to serve is greater than 0. Therefore, we will denote by $V_p^* \subseteq V^*$ the set of demand nodes with $r_i^p > d_{pi}$ in the period $p$. It can be noted that in the period $p$, those nodes belonging to $V^* \setminus V_p^*$ either have stock-out and we will make a round trip from the depot in order to supply them or they do not need to be supplied because their replenishment policy is equal to their stock available. Therefore, these nodes will not be present in the CVRP. Additionally, we will denote by $V_p$ the set $V_p^* \cup \{0\}$. In the CVRP, a fleet of delivery vehicles with uniform capacity must service customers with known demand for a single commodity. There is a traveling cost, $c_{ij} = c_{ji} > 0$ associated with moving from a facility $i$ to a different facility $j$ for all $i \in V$ and $j \in V \setminus \{i\}$. The vehicles start and end their routes at a common depot (node 0). Each customer can only be served by one vehicle. Given a fleet of vehicle $K$, the objective is to assign a sequence of customers to each vehicle $k \in K$ minimizing the total routing cost such that all customers are served and the total demand served by each vehicle does not exceed its capacity $Q$.

The formulation uses the following decision variables:

- $x_{pil}$ is a binary variable equal to 1 if policy $l$ is applied to customer $i \in V^*$ in period $p \in P$.
- $y_{ij}^{pk}$ is a binary variable equal to 1 if the edge connecting node $i \in V_p$ and $j \in V_p \setminus \{i\}$ is traversed at period $p \in P$ by a vehicle $k \in K$.

$$\text{Minimize} \sum_{p\in P} \left( \sum_{i\in V^*} f\left( \sum_{l=1}^{m} r_{il} x_{pil}, d_{pi} \right) + \sum_{i\in V_p} \sum_{j\in V_p\setminus\{i\}} \sum_{k\in K} c_{ij} y_{ij}^{pk} \right) \tag{3.2}$$

subject to

$$\sum_{l=1}^{m} x_{pil} = 1, \qquad \forall p \in P, \forall i \in V^* \tag{3.3}$$

$$l^0_{(p+1)i} = \max\left\{ \sum_{l=1}^{m} r_{il} x_{pil} - d_{pi}, 0 \right\} \quad \forall p \in P \setminus \{1\}, \forall i \in V^* \tag{3.4}$$

$$\sum_{l=1}^{m} r_{il} x_{pil} \geq l^0_{pi}, \qquad \forall p \in P, \forall i \in V^* \tag{3.5}$$

$$\sum_{k\in K} \sum_{i\in V_p\setminus\{j\}} y_{ij}^{pk} = 1, \qquad \forall p \in P, \forall j \in V_p^* \tag{3.6}$$

$$\sum_{j\in V_p^*} y_{0j}^{pk} \leq 1, \qquad \forall p \in P, \forall k \in K \tag{3.7}$$

$$\sum_{i\in V_p\setminus\{j\}} y_{ij}^{pk} = \sum_{i\in V_p\setminus\{j\}} y_{ji}^{pk}, \qquad \forall p \in P, \forall k \in K, \forall j \in V_p \tag{3.8}$$

$$\sum_{i\in V_p^*} \sum_{j\in V_p^*\setminus\{i\}} d_{pi} y_{ij}^{pk} \leq Q, \qquad \forall p \in P, \forall k \in K \tag{3.9}$$

$$\sum_{k\in K} \sum_{i\in S} \sum_{j\in S\setminus\{i\}} d_{pi} y_{ij}^{pk} \leq |S| - 1, \qquad \forall p \in P, \forall S \subseteq V_p^* \tag{3.10}$$

$$x_{pil} \in \{0,1\} \qquad \forall p \in P, \forall i \in V^*, l \in \{1,2,\ldots,m\} \tag{3.11}$$

$$y_{ij}^{pk} \in \{0,1\} \qquad \forall p \in P, \forall k \in K, \forall i \in V_p, \forall j \in V_p \setminus \{i\} \tag{3.12}$$

The objective function (3.2) simultaneously sets the $x_{pil}$ and $y_{ij}^{pk}$ decision variables in order to minimize the inventory and routing cost. The model constraints (3.3) assure that only one policy is applied to the customer $i \in V^*$ in the period $p \in P$. The constraints (3.4) determine initial stock level $l_{(p+1)i}^{0}$ for the next period $p+1$. The constraints (3.5) are imposed in order to ensure that the replacement policy that we decided to maintain in node $i \in V^*$ for the period $p$ is at least the initial stock $l_{pi}^{0}$. The model constraints (3.6) are the degree constraints and ensure that each customer is visited by exactly one vehicle. The flow constraints (3.7) and (3.8) guarantee that each vehicle can leave the depot only once, and the number of the vehicles arriving at every customer and entering the depot is equal to the number of the vehicles leaving. In the constraints (3.9) the capacity constraints are stated, making sure that the sum of the demands of the customers visited in a route is less than or equal to the capacity of the vehicle performing the service. The sub-tour elimination constraints (3.10) ensure that the solution contains no cycles disconnected from the depot. The remaining obligatory constraints (3.11) and (3.12) specify the definition domains of the variables.

## 3.4 From a Static to a Reactive Simheuristic Approach

Our simulated environment assumes that delivered feed quantities for a given set of farms must be determined each day within a planning horizon. Given the nomenclature used in IRP literature, a silo would have a direct equivalence with a retail center (RC). This time horizon is usually defined for a few days, being the realistic time where predictions are within desired confident intervals. Feed is transported by a fleet of homogeneous vehicles of limited size. Every farm has a stochastic feed demand, while the intensity of the consumption varies over different farms. Farms store feed within silos of known capacity. Each silo has a known storing capacity, and it is equipped with a sensor that hourly communicates the stock level to a central database. Farms can be served several times a day (the observed time period). The total inventory costs are assumed to be dependent on the sum of the average stock levels in each day of the planning horizon, whereas transport costs depend on travelled distances. Regarding the refill of the silo, the basic approaches a farm can select are: full refill, refill up to 75%, refill up to 50%, refill up to 25%, or no refill at all. Figure 3.2 shows some of the replenishment policies a farm can choose, which controls how and when the silos at each farm are refilled. For instance, according to the given current stock and assuming a policy of refilling up-to-fifty-percent, the final quantity refilled for this bin would be $6,500$kg.

Moreover, figure 3.3 compares two scenarios: first, an order up-to-maximum-level strategy where trucks easily do single point trips; secondly, a strategy with service-level targets where stocks are managed by the provider to assure feed availability, as in this example, where policies to refill bin up-to-fifty percent, up-to-twenty-five percent or up-to-seventy-five percent are used.

A solution to the described problem will have the form of a matrix, with $|V^*|$ rows and $|P|$ columns. The element $(i,p)$ in this matrix represents the refill policy associated with silo $i$ at period $p$ ($\forall i \in V^*$, $\forall p \in P$).

We present a comparison between two optimization approaches to validate our hypothesis. The goal is to obtain improvements –in terms of costs reduction– by updating inventory

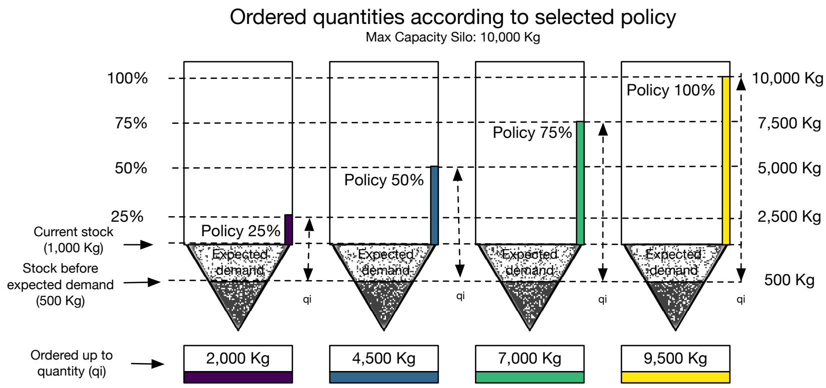



FIGURE 3.2: An illustrative example of the two strategies presented to optimize the refilling policies and frameworks.

levels for each new optimized period. For that purpose, the reference scenario makes use of the non-reactive heuristic proposed by Gruler, Panadero, Armas, Pérez, and Juan, 2020, which is used to establish a reference framework we can compare with. This non-reactive method is denoted as $M_0$. Next, a second framework, based in our reactive approach, is described as $M_1$. The non-reactive method $M_0$ sets the policy matrix by optimizing the whole set of periods at the same time. The reactive method $M_1$ updates the inventory stock in each period and then re-optimizes for the remaining periods.

### 3.4.1 Non-reactive (Static) Simheuristic Approach

The reference scenario consists of three different stages. Firstly, a constructive heuristic is employed to generate an initial solution. This initial solution will be a 'homogeneous' matrix containing the same value in all its cells, i.e., it will propose a unique refill policy that will be systematically applied to all the customers across the different periods. This strategy will generate an expected inventory cost (sum of all expected inventory costs for each customer-period combination) as well as an expected routing cost (sum of all expected routing costs for each period). Notice that both the inventory cost associated with each customer at the end of period $p$ as well as the routing cost at period $p+1$ will depend on the precise values of the random demands of each customer at period $p$ (since these values will determine the inventory levels associated with each customer at the end of period $p$). Secondly, the constructive heuristic is integrated into a biased-randomized framework. The use of non-uniform random elements to better guide the searching process in vehicle routing problems was initially proposed in Faulin and Juan, 2008 and Faulin, Gilibert, Juan, Vilajosana, and Ruiz, 2008 and then successfully used in solving different vehicle routing problems (Dominguez, Juan, Nuez, and Ouelhadj, 2016; Martin, Ouelhadj, Beullens, Ozcan, Juan, and Burke, 2016). Finally, it is extended into a simheuristic by integrating Monte Carlo simulation (MCS) in order to account for uncertainty in the demands (Grasas, Juan, and Lourenço, 2016; Ferone, Gruler, Festa, and Juan, 2019). MCS is employed here to generate realizations of the random demands and then obtain an estimate of both expected inventory and routing costs. Finally, a refinement stage using a higher number of simulation runs is applied to the most 'promising' solutions obtained in the previous stage in order to obtain a more accurate estimation of the expected cost and select the final solution matrix.

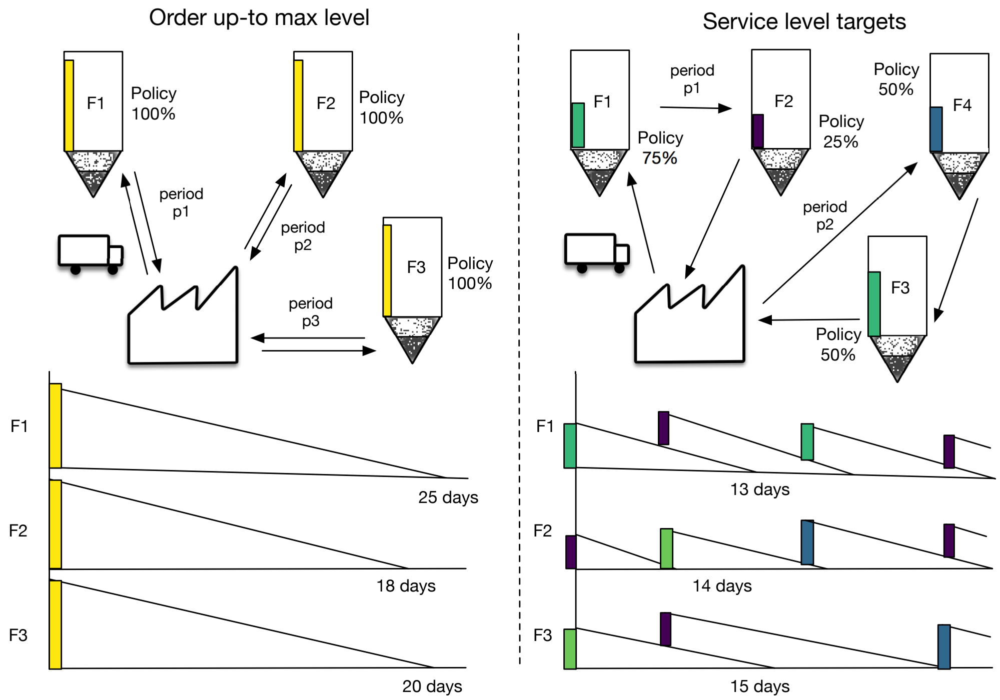



FIGURE 3.3: An illustrative example of the two strategies presented to optimize the refilling policies and frameworks.

### 3.4.2 Reactive (Dynamic) Simheuristic Approach

As previously stated, the initial solution in the non-reactive approach is represented by a homogeneous matrix containing the same value in all its cells. The goal now is to improve this initial matrix by considering our IRP scenario as a dynamic problem were decisions are iteratively made as new customers' demands are gradually revealed over time (Berbeglia, Cordeau, and Laporte, 2010). With this goal in mind, we have developed a second approach. It performs a multi-period optimization, dealing with stochastic demands. It also makes use of the inventory level at each customer by the end of each period. Of course, strategies selected for the previous periods are immutable, while the $p + 1$ and future periods are re-evaluated. The idea then is to analyze how this 'reactive optimization' improves the results obtained when compared with the more static approach that we use as a reference. The dynamic approach is implemented in two different ways: the 'reactive' scenario and the 'demand-based' scenario. The former has been explained already, while the latter lead us to the point of exploring another *what-if* scenario: for each period and customer, the demand-based approach chooses the policy that meets the expected demand. It is still a multi-period dynamic optimization approach that generates heterogeneous policy matrices.

With the aim of generating an initial 'non-homogeneous' solution matrix, a constructive heuristic has been developed. Figure 3.4 shows an illustrative example of the two strategies presented to optimize the refilling policies and their comparison with the non-reactive method. With the non-reactive strategy ($M_0$), the policy matrix computed according to a multi-period approach is applied for the whole time window. The reactive approach ($M_1$) adjusts the initially generated policy matrix according to consolidated demands for each period. Finally, the demand-based strategy ($M_2$) adjusts policies to match expected demand at each period and silo.

For the reactive scenario, the policy selected will be the one providing the lowest expected total cost, which will include both expected inventory and routing costs. The heuristic is split in two phases. During the first one, different refill policies are tested, and the associated quantities to serve are estimated together with the expected inventory costs. During the second phase, routing costs are computed for each of these refill policies. In this phase, the quantities to serve generated in the previous phase are used. Finally, the policy providing the lowest total expected cost is implemented for all customers in each period.

For the demand-based scenario, the optimization procedure is performed as many times as periods are being considered.

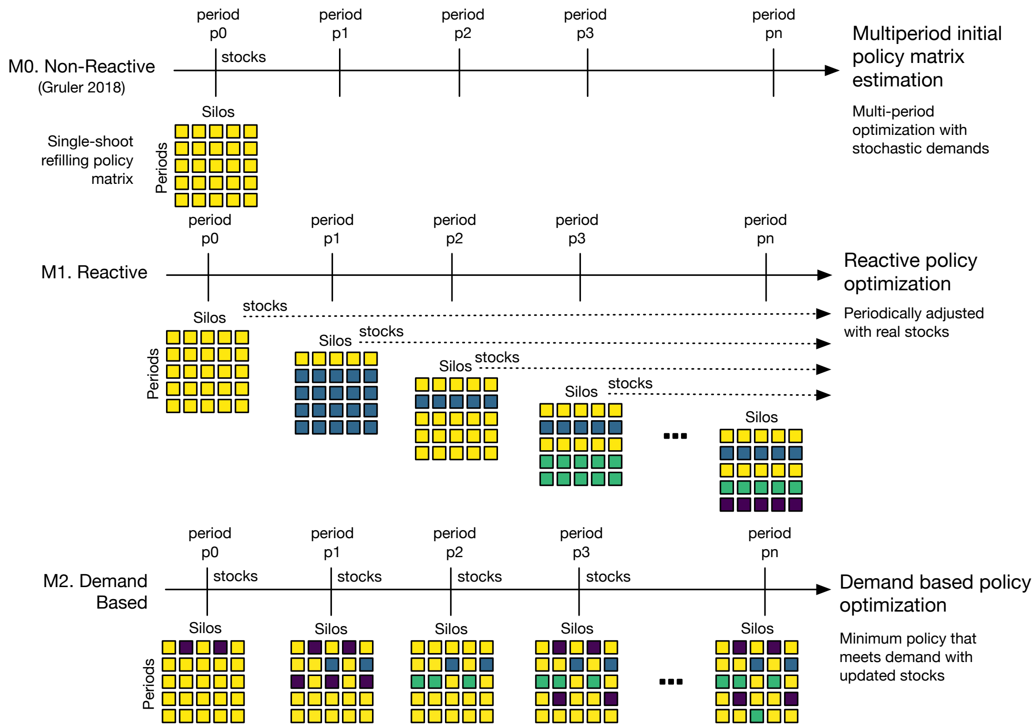



FIGURE 3.4: Presented strategies and its comparison with the non-reactive method. Colour coding yellow-lighter (100% refill strategy) to purple-darker (No refill strategy) depicts the distinct replenishment strategies used.

Algorithms 2 and 3 depict the reactive approach in more detail. The input parameters are: the set of customers, the set of time periods, the initial inventory levels, the maximum storage capacity of each customer, the random demand of each customer at each time period, the set of refill policies, and the maximum number of simulation runs that must be executed. The possible refill policies considered are:

- *Policy 0*: No stock refill, i.e., the customer can only count on its current stock level to satisfy the demand during the next period.
- *Policy 1*: Refill up to one quarter of total capacity (1/4-refill), i.e., if necessary, additional product will be served from the depot to reach that level.
- *Policy 2*: Refill up to half of total capacity (1/2-refill).
- *Policy 3*: Refill up to three quarters of total capacity (3/4-refill).
- *Policy 4*: Refill up to full capacity (full refill).

**Inputs:**
$V = \{0, 1, \ldots, |V|\}$: Set of depot (0) and customers ($V^*$)
$P = \{1, 2, \ldots, |P|\}$: Set of time periods
$L^0_{i1}$: Initial inventory level of customer $i$ at period 1
$l^+_i$: Maximum storage capacity of customer $i$
$D_{ip}$: Customers' aggregated demand at customer $i$ during period $p$
$T$: Refill policies as a % of $l^+_i$ (e.g., 0%, 25%, 50%, 75%, 100%)
$maxRuns$: Maximum number of runs in the Monte Carlo simulation
% Phase 1: Compute avg. multi-period inventory costs for each center-policy combination

```
1  foreach refill policy t ∈ T do
2  |   expInvCost[t] ← 0        % expected inventory cost associated with policy t
   end
3  foreach period p ∈ P do
4  |   previousPeriods ← previousPeriods ∪ {p}
5  |   foreach RC i ∈ V* do
6  |   |   accumInvCost ← 0
7  |   |   foreach refill policy t ∈ T do
8  |   |   |   iter ← 0
9  |   |   |   while iter < maxRuns do
10 |   |   |   |   foreach currentPeriod cp ∈ {P - previousPeriods } do
11 |   |   |   |   |   q_{i,cp}[t][iter] ← max{t · l^+_i − L^0_{i,cp}, 0}
12 |   |   |   |   |   d_{i,cp} ← generate random observation of D_{i,cp}        % Monte Carlo
   |   |   |   |   |     simulation
13 |   |   |   |   |   L^0_{i,cp+1} ← max{L^0_{i,cp} + q_{i,cp}[t][iter] − d_{i,cp}, 0}
14 |   |   |   |   |   invCost ← computeInventoryCost(t, L^0_{i,cp+1})
15 |   |   |   |   |   accumInvCost ← accumInvCost + invCost
   |   |   |   |   end
16 |   |   |   |   iter ← iter + 1
   |   |   |   end
17 |   |   |   avgInvCostCostumer ← accumInvCost/maxRuns        % avg. inventory cost
   |   |   |     of customer i under policy t
18 |   |   |   expInvCost[t] ← expInvCost[t] + avgInvCostCostumer
19 |   |   |   foreach Period p ∈ P do
20 |   |   |   |   avgInvCostPeriod[i][t][p] ← stockCostPeriod[t][p]/maxRuns        % avg.
   |   |   |   |     inventory cost of customer i under policy t and period p
21 |   |   |   |   expInvCostPeriod[t][p] ←
   |   |   |   |     expInvCostPeriod[t][p] + avgInvCostPeriod[i][t][p]
   |   |   |   end
   |   |   end
   |   end
22 |   [initSo] ←
   |     doPhase2(previousSol, estimateRoutingCost, routingCostPeriod, routingCostPeriod, expInvCostPeriod)
   end
23 return initSol
```

**Algorithm 2:** Reactive - Phase 1: Compute avg. multi-period inventory costs for each center-policy combination

Hence, for a given period $p$, a full optimization of the range $p, p+1, \ldots, |P|$ is evaluated to select the appropriate policies. Also, for each period $p$, and for each policy and customer, a short number of simulation runs is executed (e.g., 30 to 50 runs) to obtain initial estimates of costs. During each of these runs, the quantity to be served is obtained for each customer-period combination (line 11). This quantity is used in the second phase of the heuristic, and is computed considering the maximum storage capacity of the customer and its initial inventory level. For each customer and period, the specific value of the

**Inputs:**
$V = \{0, 1, \ldots, |V|\}$: Set of depot (0) and customers ($V^*$)
$P = \{1, 2, \ldots, |P|\}$: Set of time periods
$L^0_{i1}$: Initial inventory level of customer $i$ at period 1
$l^+_i$: Maximum storage capacity of customer $i$
$D_{ip}$: Customers' aggregated demand at customer $i$ during period $p$
$T$: Refill policies as a % of $l^+_i$ (e.g., 0%, 25%, 50%, 75%, 100%)
$maxRuns$: Maximum number of runs in the Monte Carlo simulation
% Phase 2: Compute avg. multi-period routing cost and total cost for each policy

```
1  initSol ← previousSol
2  cost(initSol) ← ∞
3  foreach refill policy t in T do
4      accumRoutingCost ← 0
5      iter ← 0
6      while iter < maxRuns do
7          foreach period p ∈ P do
8              routingCost ← estimateRoutingCost(q_1p[t][iter], ..., q_|V|p[t][iter])      % use
                 savings heuristic
9              accumRoutingCost ← accumRoutingCost + routingCost
10             routingCostPeriod[t][p] ← routingCostPeriod[t][p] + accumRoutingCost
           end
11         iter ← iter + 1
       end
12     expRoutingCost[t] ← accumRoutingCost / maxRuns
13     totalCost[t] ← expInvCost[t] + expRoutingCost[t]
14     foreach currentPeriod cp ∈ {P - previousPeriods } do
15         routingCostPeriod[t][p] = routingCostPeriod[t][p] / maxSim
16         allSols[t] ← stockCostPeriod(expInvCostPeriod[t][p], currentPeriod
17         allSols[t] ← routingCostPeriod(routingCostPeriod[t][p], currentPeriod
       end
18     allSols[t] ← {} if totalCost[t] < cost(initSol) then
19         bestPolicy ← t
20         foreach Period p ∈ P do
21             initSol ← setAllRefillDecisionsToValue(t)
22             cost(initSol) ← totalCost
           end
       end
   end
23 return initSol
```

**Algorithm 3:** Reactive - Phase 2: Compute avg. multi-period routing cost and total cost for each policy

random aggregated demand is generated using random sampling (line 12). Hence, it is possible to compute the inventory level at the end of the current period (line 13), which will be the initial inventory level for the next period. This is given by the sum of the initial inventory level and the quantity served minus the aggregated customer demand. In the case a stock out occurs, a penalty cost is applied and the final inventory level is set to 0 (it can never be negative at the beginning of a new period). Notice that the system evolves considering the dependencies between the realization of the demands at one period and the inventory levels at the beginning of the next one. Finally, the inventory cost is computed (line 14) for each customer and policy. If a stock out occurs, the cost of a round trip to the depot is charged as part of the inventory cost. Otherwise, the inventory cost is obtained as the number of units in stock multiplied by a $\lambda$ parameter. Following Juan, Faulin, Caceres-Cruz, Barrios, and Martinez, 2014, we have considered four distinct values for $\lambda = \{0.01, 0.25, 0.50, 0.75\}$ in our computational experiments. This process (lines 9 to 18) is repeated until the total number of simulation runs has been reached. Inventory costs are accumulated in each run (line 15), and then average inventory costs are computed for each customer (line 17). The resulting value is added to the total expected inventory cost associated with the current policy (line 18). At phase 3 of this algorithm, the expected inventory cost for each considered replenishment policy is obtained. Also, the computed quantities to serve, for each customer and period, are stored in each simulation run. These quantities are used to estimate the expected routing cost associated with each policy. Thus, for each series of delivery quantities a biased-randomized routing heuristic is employed to estimate the associated routing cost (line 8). As discussed in (Juan, Faulín, Jorba, Riera, Masip, and Barrios, 2011), a geometric distribution with parameter $\beta$ $(0 < \beta < 1)$ is used to define the probabilities of including each edge in the routing solution.

Finally, the expected routing cost is computed (line 12). At the end of this phase, the policy involving the lowest expected total cost (inventory plus routing) is chosen.

## 3.5 Computational Experiments and Analysis of Results

A set of computational experiments has been performed to test our reactive approach and measure how it can improve over the non-reactive method proposed by Gruler, Panadero, Armas, Pérez, and Juan, 2020. The set of 27 vehicle routing problem instances proposed by Augerat, Belenguer, Benavent, Corberán, Naddef, and Rinaldi, 1995 and adapted for the IRP by Juan, Faulin, Caceres-Cruz, Barrios, and Martinez, 2014 are used as a testbed. These instances contain between 27 and 80 nodes, a single central depot, and a fleet of 5 to 10 homogeneous vehicles. The algorithm was implemented as a Java application and executed with the following parameter specifications:

- Inventory holding cost: $\lambda \in \{0.01, 0.25, 0.50, 0.75\}$
- Stopping criterion: 100 seconds $\times$ number of considered periods.
- Number of simulation runs in Phase 1: 30.
- Four different random seeds were used during the tests.

The geometric distribution parameter $\beta$ during the routing phase is randomly selected in the interval $[0.2, 0.3]$. The aggregated customers' demands are assumed to follow a log-normal probability distribution with the same average values as the ones proposed in the original instances. The log-normal and Weibull are flexible probability distributions that can be used to model non-negative random variables. Hence, both distributions are frequently used to model variables such as times-to-failure (duration) or demands (Juan, Faulín, Jorba, Riera, Masip, and Barrios, 2011; Cobb, Rum, and Salmer, 2013). In a real-life application, historical observations would be fitted by the proper probability distribution using statistical methods and goodness-of-fit tests. Notice, however, that our simheuristic approach does not depend on the specific probability distribution employed to model the customers' demands. In other words, any other distribution could be used instead without affecting the general procedure. Four demand factors, $\gamma \in \{0.05, 0.1, 0.3, 1\}$, have been considered to decrease this demand. The expected demand for each customer is assumed to be 50% of its maximum capacity. Then, as a resulting of applying $\gamma$ factors to demands distributions, it turns into five distinct demand scenarios with averages 2.5%, 5%, 15%, and 50% of the maximum capacity. Considering each of this demand scenarios, three different variance levels are defined: low ($factor = 0.25$), medium ($factor = 0.50$), and large ($factor = 0.75$). In addition, four different planning horizons are analyzed, covering

3, 5, 7, and 10 time periods, respectively. The number of customers and vehicles in each instance are reflected in its name.

Tables 3.1–3.3, show the numerical results obtained by using the two presented approaches in terms of total cost. The average total costs over all instances for each variance level, demand factor, and planning horizon of the holistic multi-period planning framework can be seen in Figures 3.5–3.7. Accumulated routing and inventory costs are depicted for the non-reactive approach proposed by Gruler, Panadero, Armas, Pérez, and Juan, 2020 –in which the same replenishment policy is applied for all customers in each individual period. Likewise, solutions found by the two proposed simheuristic methods for the multi-period IRP (reactive and demand based) are also provided. In both approaches, increasing costs can be observed with higher levels of demand-uncertainty, which can be explained by higher inventory (holding or stock-out) costs.

TABLE 3.1: Comparison our best solution to initial solution total cost ( *Variance level = 0.25*, *Demand factor = 0.1 (5% total capacity)*, *Inventory holding cost($\lambda$ = 0.25)*.

| | Periods : 3 | | | | | Periods : 5 | | | | | Periods : 7 | | | | | Periods : 10 | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | NR (1) | Reactive (2) | Demand Based (3) | %-Gap (1)-(2) | %-Gap (1)-(3) | NR (4) | Reactive (5) | Demand Based (6) | %-Gap (4)-(5) | %-Gap (4)-(6) | NR (7) | Reactive (8) | Demand Based (9) | %-Gap (7)-(8) | %-Gap (7)-(9) | NR (10) | Reactive (11) | Demand Based (12) | %-Gap (10)-(11) | %-Gap (10)-(12) |
| **A-n32-k5** | 1385 | 463 | 1133 | -66.6 | -18.2 | 2397 | 1150 | 1604 | -52.0 | -33.1 | 3488 | 2489 | 2640 | -28.7 | -24.3 | 5114 | 3988 | 3364 | -22.0 | -34.2 |
| **A-n33-k5** | 1286 | 461 | 1137 | -64.1 | -11.6 | 2240 | 1426 | 1578 | -36.3 | -29.6 | 3480 | 1584 | 2462 | -54.5 | -29.3 | 5048 | 3197 | 3398 | -36.7 | -32.7 |
| **A-n33-k6** | 1475 | 629 | 1213 | -57.4 | -17.7 | 2565 | 1567 | 1686 | -38.9 | -34.3 | 3733 | 1845 | 2800 | -50.6 | -25.0 | 5508 | 3434 | 3614 | -37.7 | -34.4 |
| **A-n37-k5** | 1403 | 712 | 1024 | -49.3 | -27.0 | 2374 | 1581 | 1400 | -33.4 | -41.0 | 3412 | 1565 | 2316 | -54.1 | -32.1 | 5174 | 4257 | 3353 | -17.7 | -35.2 |
| **A-n38-k5** | 1736 | 703 | 1230 | -59.5 | -29.2 | 3026 | 1836 | 1623 | -39.3 | -46.4 | 4405 | 2209 | 2866 | -49.8 | -34.9 | 6463 | 4392 | 3990 | -32.0 | -38.3 |
| **A-n39-k6** | 1684 | 1027 | 1344 | -39.0 | -20.2 | 2800 | 2159 | 1893 | -22.9 | -32.4 | 3982 | 1786 | 2907 | -55.1 | -27.0 | 5910 | 4857 | 4094 | -17.8 | -30.7 |
| **A-n45-k6** | 1691 | 641 | 1442 | -62.1 | -14.7 | 3048 | 1924 | 1983 | -36.9 | -35.0 | 4327 | 3105 | 3375 | -28.2 | -22.0 | 6411 | 5032 | 4678 | -21.5 | -27.0 |
| **A-n45-k7** | 1794 | 595 | 1778 | -66.8 | -0.9 | 3238 | 1429 | 2317 | -55.8 | -28.4 | 4689 | 3363 | 3731 | -28.3 | -20.4 | 7147 | 5804 | 4964 | -18.8 | -30.6 |
| **A-n55-k9** | 1975 | 804 | 1960 | -59.3 | -0.7 | 3374 | 2282 | 2617 | -32.4 | -22.4 | 4833 | 3793 | 4162 | -21.5 | -13.9 | 7196 | 5680 | 5440 | -21.1 | -24.4 |
| **A-n60-k9** | 1990 | 936 | 2062 | -53.0 | 3.6 | 3392 | 2230 | 2792 | -34.2 | -17.7 | 4972 | 3718 | 4676 | -25.2 | -6.0 | 7189 | 5830 | 6052 | -18.9 | -15.8 |
| **A-n61-k9** | 1744 | 834 | 1679 | -52.2 | -3.7 | 3008 | 2058 | 2430 | -31.6 | -19.2 | 4373 | 2536 | 3893 | -42.0 | -11.0 | 6536 | 5109 | 5251 | -21.8 | -19.7 |
| **A-n63-k9** | 2492 | 1006 | 2350 | -59.6 | -5.7 | 4266 | 2032 | 3129 | -52.4 | -26.7 | 6145 | 4624 | 5214 | -24.7 | -15.1 | 8645 | 7125 | 6603 | -17.6 | -23.6 |
| **A-n65-k9** | 2056 | 893 | 1834 | -56.6 | -10.8 | 3348 | 2208 | 2578 | -34.1 | -23.0 | 5011 | 2637 | 4288 | -47.4 | -14.4 | 7190 | 5906 | 5889 | -17.9 | -18.1 |
| **A-n80-k10** | 2505 | 1095 | 2380 | -56.3 | -5.0 | 4086 | 2078 | 3419 | -49.1 | -16.3 | 6070 | 4188 | 5182 | -31.0 | -14.6 | 8471 | 6510 | 7087 | -23.1 | -16.3 |
| **B-n31-k5** | 1377 | 459 | 1055 | -66.7 | -23.4 | 2455 | 1502 | 1431 | -38.8 | -41.7 | 3360 | 1536 | 2377 | -54.3 | -29.3 | 4980 | 4042 | 3097 | -18.8 | -37.8 |
| **B-n35-k5** | 1575 | 909 | 1404 | -42.3 | -10.8 | 2562 | 1714 | 2065 | -33.1 | -19.4 | 3659 | 2759 | 3028 | -24.6 | -17.2 | 5481 | 4121 | 3995 | -24.8 | -27.1 |
| **B-n39-k5** | 1391 | 826 | 938 | -40.6 | -32.6 | 2403 | 1601 | 1353 | -33.4 | -43.7 | 3358 | 2542 | 2321 | -24.3 | -30.9 | 4764 | 3946 | 3518 | -17.2 | -26.2 |
| **B-n41-k6** | 1538 | 616 | 1270 | -60.0 | -17.4 | 2629 | 1702 | 1749 | -35.3 | -33.5 | 3696 | 1951 | 3010 | -47.2 | -18.6 | 5321 | 4355 | 3640 | -18.2 | -31.6 |
| **B-n45-k5** | 1251 | 671 | 1147 | -46.4 | -8.3 | 2137 | 1087 | 1598 | -49.1 | -25.2 | 3180 | 1871 | 2676 | -41.1 | -15.8 | 5190 | 4304 | 3751 | -17.1 | -27.7 |
| **B-n50-k7** | 1680 | 799 | 1304 | -52.5 | -22.4 | 2836 | 1921 | 1978 | -32.3 | -30.3 | 3995 | 2060 | 2998 | -48.4 | -24.9 | 5610 | 4600 | 4062 | -18.0 | -27.6 |
| **B-n52-k7** | 1358 | 577 | 1263 | -57.5 | -7.0 | 2286 | 1242 | 1840 | -45.7 | -19.5 | 3364 | 2158 | 3060 | -35.8 | -9.1 | 4751 | 3538 | 4048 | -25.5 | -14.8 |
| **B-n56-k7** | 1358 | 759 | 1108 | -44.1 | -18.4 | 2286 | 1205 | 1613 | -47.3 | -29.5 | 3276 | 2496 | 2825 | -23.8 | -13.8 | 4653 | 3850 | 4045 | -17.3 | -13.1 |
| **B-n57-k9** | 1987 | 784 | 2174 | -60.6 | 9.4 | 3516 | 2279 | 2940 | -35.2 | -16.4 | 4871 | 3739 | 4664 | -23.2 | -4.3 | 7258 | 6154 | 5935 | -15.2 | -18.2 |
| **B-n64-k9** | 1740 | 843 | 1621 | -51.5 | -6.9 | 2815 | 1947 | 2355 | -30.8 | -16.3 | 3946 | 2303 | 3680 | -41.6 | -6.7 | 5838 | 4832 | 5178 | -17.2 | -11.3 |
| **B-n67-k10** | 1875 | 840 | 1846 | -55.2 | -1.5 | 3032 | 2056 | 2638 | -32.2 | -13.0 | 4342 | 2884 | 4197 | -33.6 | -3.3 | 6392 | 5177 | 5495 | -19.0 | -14.0 |
| **B-n68-k9** | 1411 | 794 | 1844 | -43.7 | 30.6 | 2559 | 1408 | 2558 | -45.0 | 0.0 | 3520 | 2429 | 4220 | -31.0 | 19.9 | 5040 | 3886 | 5522 | -22.9 | 9.6 |
| **B-n78-k10** | 1655 | 857 | 1974 | -48.2 | 19.3 | 2868 | 1977 | 2815 | -31.1 | -1.9 | 4050 | 3234 | 4215 | -20.1 | 4.1 | 5925 | 4551 | 6024 | -23.2 | 1.7 |
| ***Average*** | *1682* | *760* | *1538* | *-54.5* | *-9.3* | *2872* | *1763* | *2147* | *-38.5* | *-25.8* | *4131* | *2645* | *3473* | *-36.7* | *-16.3* | *6045* | *4758* | *4670* | *-21.4* | *-22.9* |

TABLE 3.2: Comparison our best solution to initial solution total cost ( *Variance level = 0.5*, *Demand factor = 0.1 (5% total capacity)*, *Inventory holding cost(λ)=0.25* ).

| | Periods : 3 | | | | | Periods : 5 | | | | | Periods : 7 | | | | | Periods : 10 | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | NR (1) | Reactive (2) | Demand Based (3) | %-Gap (1)-(2) | %-Gap (1)-(3) | NR (4) | Reactive (5) | Demand Based (6) | %-Gap (4)-(5) | %-Gap (4)-(6) | NR (7) | Reactive (8) | Demand Based (9) | %-Gap (7)-(8) | %-Gap (7)-(9) | NR (10) | Reactive (11) | Demand Based (12) | %-Gap (10)-(11) | %-Gap (10)-(12) |
| **A-n32-k5** | 1386 | 776 | 1291 | -44.0 | -6.9 | 2526 | 1610 | 1632 | -36.3 | -35.4 | 3448 | 1983 | 2697 | -42.5 | -21.8 | 5106 | 4103 | 3605 | -19.6 | -29.4 |
| **A-n33-k5** | 1288 | 484 | 1138 | -62.4 | -11.6 | 2337 | 1512 | 1642 | -35.3 | -29.7 | 3525 | 1659 | 2475 | -52.9 | -29.8 | 5035 | 3370 | 3520 | -33.1 | -30.1 |
| **A-n33-k6** | 1587 | 852 | 1327 | -46.3 | -16.4 | 2566 | 1426 | 1691 | -44.4 | -34.1 | 3850 | 1845 | 2749 | -52.1 | -28.6 | 5456 | 3598 | 3754 | -34.1 | -31.2 |
| **A-n37-k5** | 1404 | 809 | 1026 | -42.4 | -26.9 | 2469 | 1790 | 1553 | -27.5 | -37.1 | 3435 | 2270 | 2205 | -33.9 | -35.8 | 5321 | 4329 | 3308 | -18.7 | -37.8 |
| **A-n38-k5** | 1842 | 1842 | 1231 | 0.0 | -33.2 | 3078 | 1946 | 1710 | -36.8 | -44.4 | 4490 | 2211 | 2820 | -50.8 | -37.2 | 6514 | 5126 | 4160 | -21.3 | -36.1 |
| **A-n39-k6** | 1857 | 1061 | 1347 | -42.8 | -27.4 | 2892 | 1473 | 2104 | -49.1 | -27.2 | 4059 | 1815 | 2803 | -55.3 | -31.0 | 6147 | 5100 | 4213 | -17.0 | -31.5 |
| **A-n45-k6** | 1710 | 730 | 1463 | -57.3 | -14.4 | 3227 | 2121 | 2012 | -34.3 | -37.6 | 4300 | 2637 | 3298 | -38.7 | -23.3 | 6590 | 5617 | 4738 | -14.8 | -28.1 |
| **A-n45-k7** | 1795 | 633 | 1778 | -64.7 | -0.9 | 3251 | 1431 | 2557 | -56.0 | -21.3 | 4623 | 3301 | 3735 | -28.6 | -19.2 | 7208 | 5895 | 5241 | -18.2 | -27.3 |
| **A-n55-k9** | 1976 | 941 | 1962 | -52.4 | -0.7 | 3506 | 2480 | 2699 | -29.3 | -23.0 | 5009 | 2985 | 4206 | -40.4 | -16.0 | 7261 | 5646 | 5541 | -22.2 | -23.7 |
| **A-n60-k9** | 2126 | 938 | 2064 | -55.9 | -2.9 | 3394 | 2232 | 2797 | -34.2 | -17.6 | 4955 | 3778 | 4554 | -23.7 | -8.1 | 7197 | 5869 | 6087 | -18.4 | -15.4 |
| **A-n61-k9** | 1822 | 836 | 1682 | -54.1 | -7.7 | 3140 | 2189 | 2481 | -30.3 | -21.0 | 4463 | 2722 | 3822 | -39.0 | -14.4 | 6546 | 5237 | 5318 | -20.0 | -18.7 |
| **A-n63-k9** | 2494 | 1153 | 2351 | -53.8 | -5.7 | 4270 | 2301 | 3328 | -46.1 | -22.1 | 6161 | 4284 | 5559 | -30.5 | -9.8 | 8782 | 7257 | 6725 | -17.4 | -23.4 |
| **A-n65-k9** | 2058 | 1076 | 1927 | -47.7 | -6.4 | 3430 | 2312 | 2612 | -32.6 | -23.8 | 5039 | 2684 | 4289 | -46.7 | -14.9 | 7293 | 5899 | 5831 | -19.1 | -20.0 |
| **A-n80-k10** | 2506 | 1292 | 2632 | -48.5 | 5.0 | 4149 | 2950 | 3562 | -28.9 | -14.2 | 6078 | 4195 | 5652 | -31.0 | -7.0 | 8497 | 7681 | 7270 | -9.6 | -14.4 |
| **B-n31-k5** | 1379 | 461 | 1057 | -66.6 | -23.3 | 2448 | 1526 | 1616 | -37.7 | -34.0 | 3357 | 1682 | 2418 | -49.9 | -28.0 | 4980 | 4048 | 3246 | -18.7 | -34.8 |
| **B-n35-k5** | 1576 | 911 | 1406 | -42.2 | -10.8 | 2946 | 1667 | 2056 | -43.4 | -30.2 | 3994 | 2932 | 2993 | -26.6 | -25.1 | 5473 | 4273 | 4152 | -21.9 | -24.1 |
| **B-n39-k5** | 1606 | 718 | 939 | -55.3 | -41.5 | 2408 | 1381 | 1404 | -42.6 | -41.7 | 3377 | 2565 | 2432 | -24.0 | -28.0 | 4828 | 4071 | 3487 | -15.7 | -27.8 |
| **B-n41-k6** | 1539 | 860 | 1271 | -44.1 | -17.4 | 2696 | 1312 | 1918 | -51.3 | -28.9 | 3830 | 1942 | 2981 | -49.3 | -22.2 | 5565 | 4437 | 4046 | -20.3 | -27.3 |
| **B-n45-k5** | 1397 | 742 | 1184 | -46.9 | -15.3 | 2208 | 1088 | 1697 | -50.7 | -23.2 | 3208 | 2203 | 2638 | -31.3 | -17.8 | 5230 | 4343 | 3940 | -17.0 | -24.7 |
| **B-n50-k7** | 1681 | 800 | 1304 | -52.4 | -22.4 | 2942 | 2021 | 2044 | -31.3 | -30.5 | 4000 | 2119 | 3062 | -47.0 | -23.5 | 5904 | 4828 | 4338 | -18.2 | -26.5 |
| **B-n52-k7** | 1358 | 624 | 1264 | -54.1 | -6.9 | 2414 | 1370 | 2122 | -43.3 | -12.1 | 3504 | 2459 | 3304 | -29.8 | -5.7 | 4899 | 3754 | 4244 | -23.4 | -13.4 |
| **B-n56-k7** | 1554 | 1097 | 1279 | -29.4 | -17.7 | 2322 | 1535 | 1875 | -33.9 | -19.3 | 3380 | 2569 | 2759 | -24.0 | -18.4 | 4693 | 3838 | 4192 | -18.2 | -10.7 |
| **B-n57-k9** | 1988 | 923 | 2176 | -53.6 | 9.5 | 3510 | 2687 | 3392 | -23.5 | -3.3 | 4984 | 3838 | 4706 | -23.0 | -5.6 | 7266 | 6442 | 5987 | -11.3 | -17.6 |
| **B-n64-k9** | 1741 | 845 | 1622 | -51.5 | -6.9 | 2864 | 1996 | 2463 | -30.3 | -14.0 | 4118 | 2400 | 3837 | -41.7 | -6.8 | 5876 | 5002 | 5205 | -14.9 | -11.4 |
| **B-n67-k10** | 1876 | 842 | 1848 | -55.1 | -1.5 | 3079 | 1677 | 2749 | -45.5 | -10.7 | 4346 | 2453 | 4194 | -43.5 | -3.5 | 6394 | 5330 | 5753 | -16.7 | -10.0 |
| **B-n68-k9** | 1552 | 872 | 1844 | -43.8 | 18.8 | 2580 | 2065 | 2876 | -20.0 | 11.5 | 3569 | 2816 | 4119 | -21.1 | 15.4 | 5150 | 4001 | 5762 | -22.3 | 11.9 |
| **B-n78-k10** | 1718 | 1212 | 1977 | -29.5 | 15.0 | 2846 | 2436 | 3026 | -14.4 | 6.3 | 4054 | 3228 | 4242 | -20.4 | 4.6 | 6019 | 5303 | 6122 | -11.9 | 1.7 |
| ***Average*** | *1734* | *901* | *1570* | *-48.0* | *-10.2* | *2944* | *1872* | *2282* | *-36.6* | *-22.9* | *4191* | *2651* | *3502* | *-37.0* | *-17.1* | *6120* | *4978* | *4807* | *-19.0* | *-21.6* |

TABLE 3.3: Comparison our best solution to initial solution total cost ( *Variance level* = *0.75*, *Demand factor* = *0.1 (5% total capacity)*, *Inventory holding cost*($\lambda$ = *0.25* ).

| | Periods : 3 | | | | | Periods : 5 | | | | | Periods : 7 | | | | | Periods : 10 | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | NR (1) | Reactive (2) | Demand Based (3) | %-Gap (1)-(2) | %-Gap (1)-(3) | NR (4) | Reactive (5) | Demand Based (6) | %-Gap (4)-(5) | %-Gap (4)-(6) | NR (7) | Reactive (8) | Demand Based (9) | %-Gap (7)-(8) | %-Gap (7)-(9) | NR (10) | Reactive (11) | Demand Based (12) | %-Gap (10)-(11) | %-Gap (10)-(12) |
| **A-n32-k5** | 1544 | 1043 | 1294 | -32.4 | -16.2 | 2539 | 1302 | 1867 | -48.7 | -26.5 | 3508 | 1985 | 2688 | -43.4 | -23.4 | 5384 | 4394 | 3536 | -18.4 | -34.3 |
| **A-n33-k5** | 1289 | 486 | 1140 | -62.3 | -11.6 | 2338 | 1513 | 1644 | -35.3 | -29.7 | 3568 | 1745 | 2460 | -51.1 | -31.1 | 5011 | 3541 | 3731 | -29.3 | -25.5 |
| **A-n33-k6** | 1588 | 923 | 1329 | -41.9 | -16.3 | 2572 | 1539 | 1724 | -40.2 | -33.0 | 3885 | 1948 | 2787 | -49.9 | -28.3 | 5446 | 3676 | 3727 | -32.5 | -31.6 |
| **A-n37-k5** | 1405 | 811 | 1027 | -42.3 | -26.9 | 2425 | 1835 | 1556 | -24.3 | -35.8 | 3495 | 2282 | 2338 | -34.7 | -33.1 | 5321 | 4352 | 3473 | -18.2 | -34.7 |
| **A-n38-k5** | 1849 | 813 | 1231 | -56.0 | -33.4 | 3080 | 1947 | 1829 | -36.8 | -40.6 | 4462 | 2072 | 2868 | -53.6 | -35.7 | 6462 | 5209 | 4211 | -19.4 | -34.8 |
| **A-n39-k6** | 1889 | 1157 | 1350 | -38.7 | -28.6 | 2894 | 1475 | 2107 | -49.0 | -27.2 | 4100 | 1823 | 2890 | -55.5 | -29.5 | 6196 | 4756 | 4190 | -23.2 | -32.4 |
| **A-n45-k6** | 1711 | 890 | 1465 | -48.0 | -14.4 | 3229 | 2144 | 2064 | -33.6 | -36.1 | 4347 | 2826 | 3370 | -35.0 | -22.5 | 6536 | 5600 | 4780 | -14.3 | -26.9 |
| **A-n45-k7** | 1832 | 781 | 1779 | -57.4 | -2.9 | 3253 | 1433 | 2625 | -55.9 | -19.3 | 4723 | 3474 | 3891 | -26.5 | -17.6 | 7366 | 6202 | 5374 | -15.8 | -27.0 |
| **A-n55-k9** | 1977 | 1047 | 1963 | -47.0 | -0.7 | 3510 | 2450 | 2806 | -30.2 | -20.1 | 5028 | 3312 | 4252 | -34.1 | -15.4 | 7281 | 5749 | 5589 | -21.0 | -23.2 |
| **A-n60-k9** | 2128 | 940 | 2066 | -55.8 | -2.9 | 3402 | 1978 | 2831 | -41.9 | -16.8 | 5102 | 3838 | 4576 | -24.8 | -10.3 | 7281 | 5976 | 6208 | -17.9 | -14.7 |
| **A-n61-k9** | 1824 | 951 | 1683 | -47.9 | -7.7 | 3154 | 2204 | 2470 | -30.1 | -21.7 | 4566 | 2730 | 3799 | -40.2 | -16.8 | 6610 | 5190 | 5607 | -21.5 | -15.2 |
| **A-n63-k9** | 2495 | 1323 | 2352 | -47.0 | -5.7 | 4420 | 2430 | 3529 | -45.0 | -20.1 | 6283 | 4698 | 5439 | -25.2 | -13.4 | 8724 | 7309 | 6739 | -16.2 | -22.8 |
| **A-n65-k9** | 2060 | 1078 | 1928 | -47.7 | -6.4 | 3456 | 2322 | 2715 | -32.8 | -21.4 | 5043 | 2697 | 4190 | -46.5 | -16.9 | 7366 | 6012 | 5985 | -18.4 | -18.7 |
| **A-n80-k10** | 2506 | 1415 | 2631 | -43.5 | 5.0 | 4166 | 2304 | 3775 | -44.7 | -9.4 | 6210 | 5637 | 5717 | -9.2 | -7.9 | 8773 | 8050 | 7202 | -8.2 | -17.9 |
| **B-n31-k5** | 1380 | 562 | 1058 | -59.3 | -23.3 | 2449 | 1526 | 1630 | -37.7 | -33.4 | 3359 | 1684 | 2442 | -49.9 | -27.3 | 5020 | 3603 | 3445 | -28.2 | -31.4 |
| **B-n35-k5** | 1578 | 913 | 1408 | -42.1 | -10.8 | 2956 | 2368 | 2205 | -19.9 | -25.4 | 3921 | 3092 | 3193 | -21.1 | -18.6 | 5428 | 4412 | 4094 | -18.7 | -24.6 |
| **B-n39-k5** | 1606 | 775 | 939 | -51.7 | -41.5 | 2410 | 1383 | 1580 | -42.6 | -34.4 | 3477 | 2491 | 2400 | -28.4 | -31.0 | 4844 | 4509 | 3682 | -6.9 | -24.0 |
| **B-n41-k6** | 1573 | 862 | 1272 | -45.2 | -19.1 | 2694 | 1366 | 2074 | -49.3 | -23.0 | 3841 | 1946 | 2997 | -49.3 | -22.0 | 5615 | 4571 | 4140 | -18.6 | -26.3 |
| **B-n45-k5** | 1433 | 778 | 1186 | -45.7 | -17.2 | 2209 | 1089 | 1754 | -50.7 | -20.6 | 3409 | 2373 | 2651 | -30.4 | -22.2 | 5291 | 4380 | 4164 | -17.2 | -21.3 |
| **B-n50-k7** | 1681 | 920 | 1305 | -45.3 | -22.4 | 2901 | 2140 | 1999 | -26.2 | -31.1 | 3995 | 1990 | 3060 | -50.2 | -23.4 | 5902 | 4964 | 4472 | -15.9 | -24.2 |
| **B-n52-k7** | 1405 | 761 | 1265 | -45.8 | -9.9 | 2533 | 1372 | 2193 | -45.8 | -13.4 | 3660 | 2635 | 3448 | -28.0 | -5.8 | 4955 | 3900 | 4442 | -21.3 | -10.4 |
| **B-n56-k7** | 1556 | 1099 | 1281 | -29.4 | -17.7 | 2490 | 1897 | 2127 | -23.8 | -14.6 | 3338 | 2340 | 2941 | -29.9 | -11.9 | 4823 | 4021 | 4132 | -16.6 | -14.3 |
| **B-n57-k9** | 2126 | 1135 | 2177 | -46.6 | 2.4 | 3617 | 2879 | 3440 | -20.4 | -4.9 | 4988 | 3559 | 4617 | -28.7 | -7.4 | 7426 | 5954 | 6445 | -19.8 | -13.2 |
| **B-n64-k9** | 1742 | 929 | 1622 | -46.7 | -6.9 | 2967 | 2100 | 2462 | -29.2 | -17.0 | 4143 | 2552 | 3773 | -38.4 | -8.9 | 5884 | 5014 | 5235 | -14.8 | -11.0 |
| **B-n67-k10** | 1878 | 940 | 1957 | -49.9 | 4.2 | 3087 | 1679 | 2778 | -45.6 | -10.0 | 4386 | 2456 | 4230 | -44.0 | -3.6 | 6380 | 5407 | 5813 | -15.3 | -8.9 |
| **B-n68-k9** | 1630 | 873 | 1845 | -46.4 | 13.2 | 2586 | 2068 | 3071 | -20.0 | 18.8 | 3645 | 2901 | 4277 | -20.4 | 17.3 | 5167 | 4030 | 5792 | -22.0 | 12.1 |
| **B-n78-k10** | 1720 | 1215 | 1978 | -29.4 | 15.0 | 2933 | 2509 | 3165 | -14.4 | 7.9 | 4173 | 3064 | 4334 | -26.6 | 3.9 | 6210 | 5607 | 6164 | -9.7 | -0.7 |
| ***Average*** | *1756* | *942* | *1575* | *-46.3* | *-11.2* | *2973* | *1898* | *2371* | *-36.1* | *-20.7* | *4246* | *2746* | *3542* | *-36.1* | *-17.1* | *6174* | *5051* | *4903* | *-18.5* | *-20.7* |

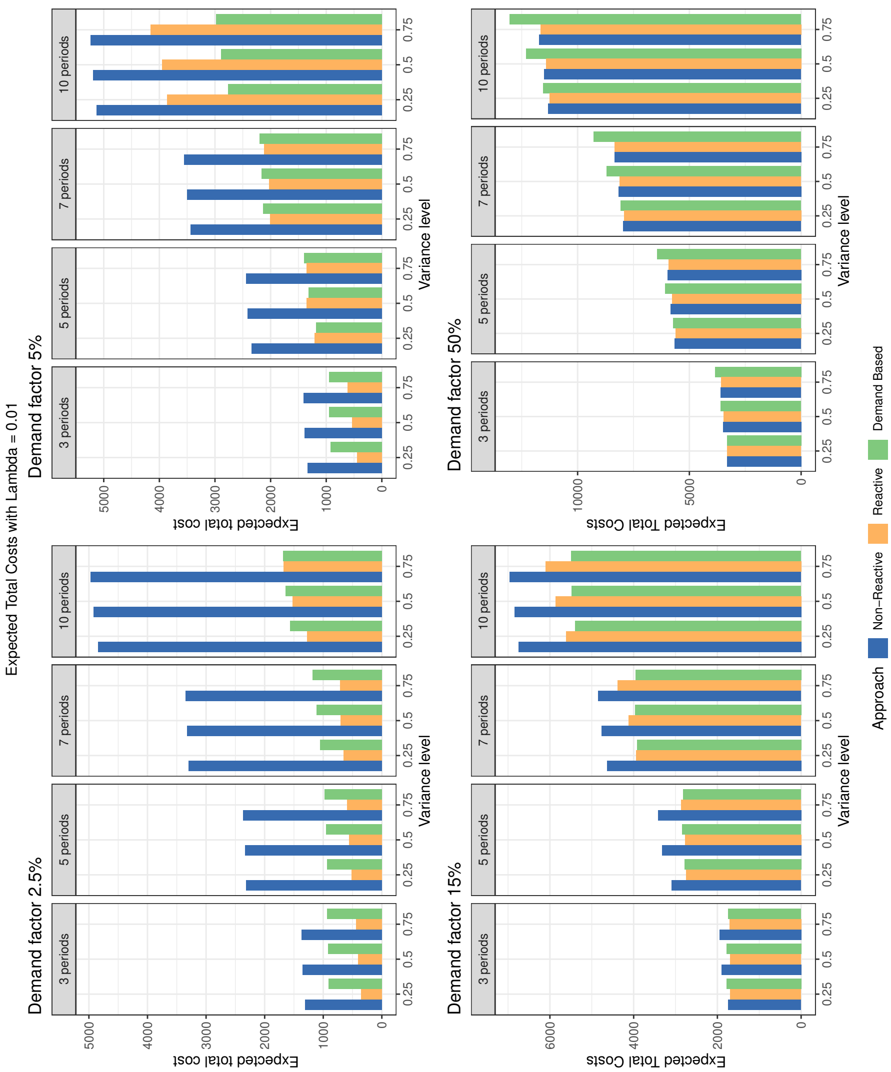



FIGURE 3.5: Expected total costs over all instances for different variance levels and planning horizons with $\lambda = 0.01$.

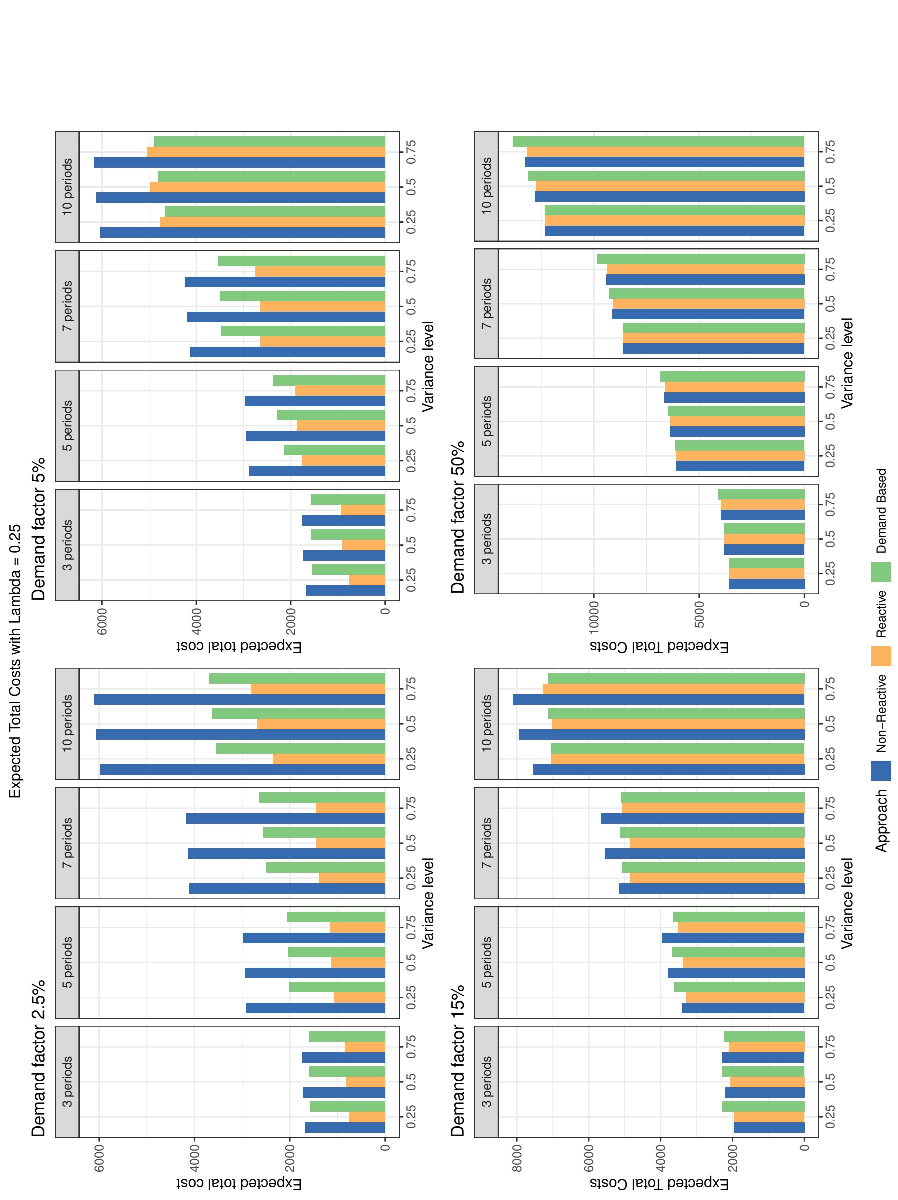



FIGURE 3.6: Expected total costs over all instances for different variance levels and planning horizons with $\lambda = 0.25$.

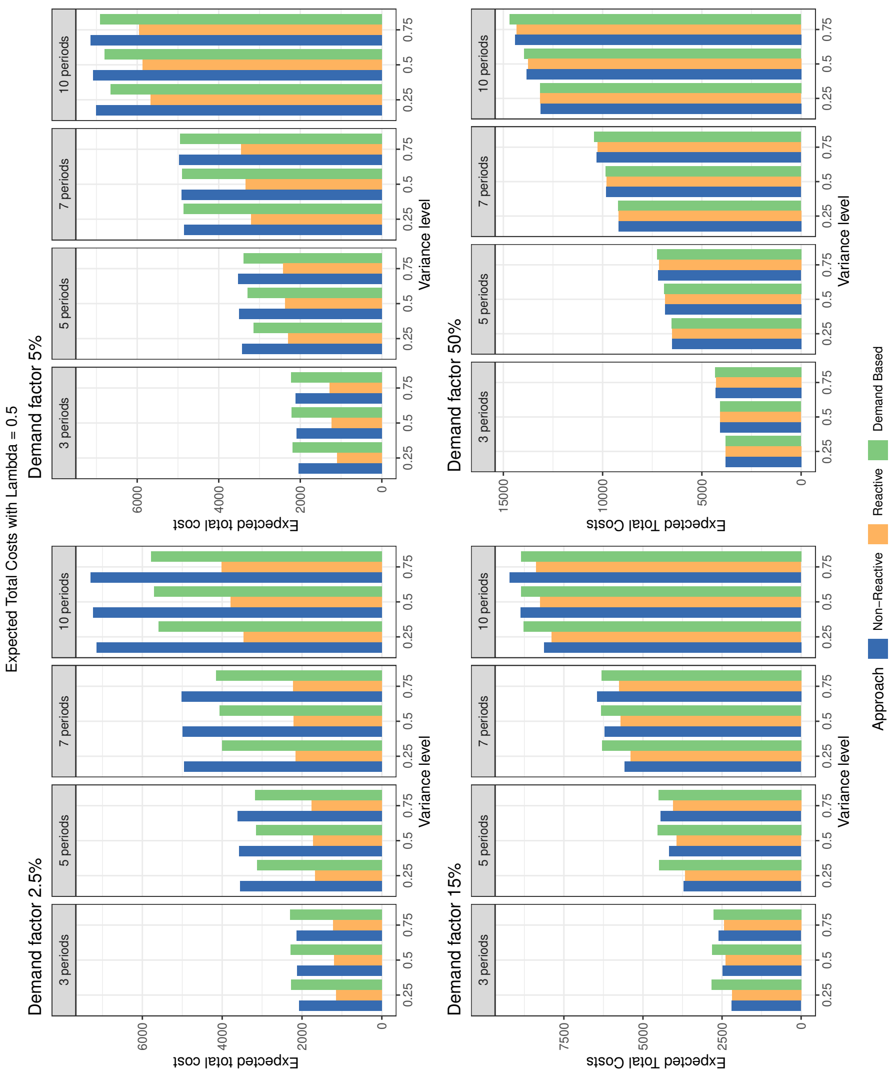



Figure 3.7: Expected total costs over all instances for different variance levels and planning horizons with $\lambda = 0.5$

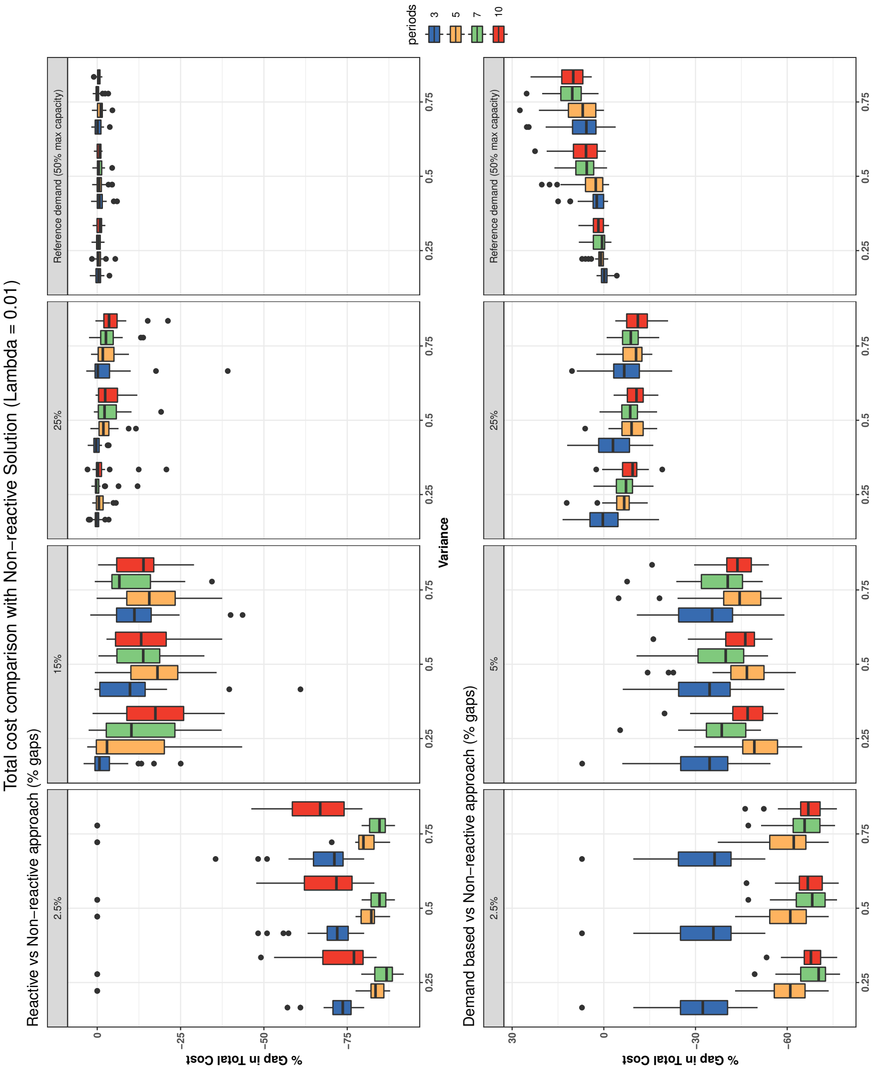



FIGURE 3.8: Comparison lambda = 0.01

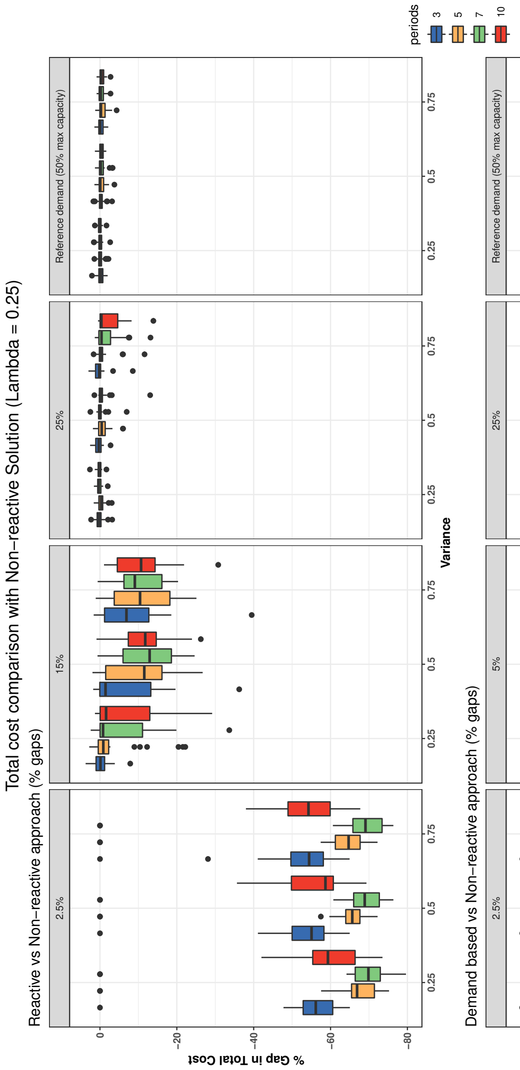



FIGURE 3.9: Comparison lambda = 0.25

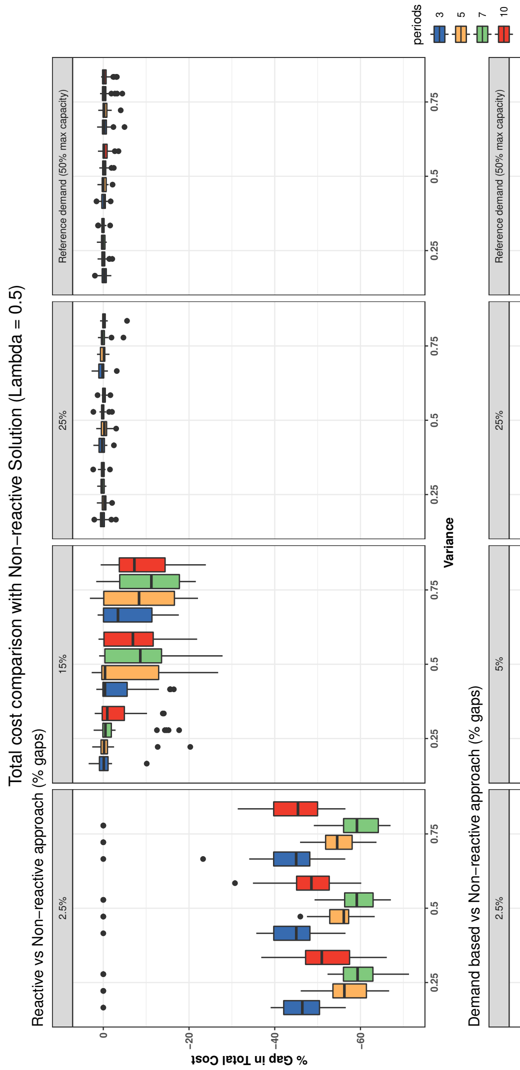



FIGURE 3.10: Comparison lambda = 0.5

Notice that in order to make a fair comparison between the $M_0$ (non-reactive), $M_1$ (reactive), and the $M_2$ (demand-based) scenarios, one should use the same observations for the stochastic demands in each period. Figure 3.11 shows the resulting policy matrices obtained for a particular instance, where each dot represents the refill policy for a particular customer-period combination. As expected, as soon as the demand decreases, distinct refilling policies become feasible apart from the "refill-up-to-full-capacity" policy.

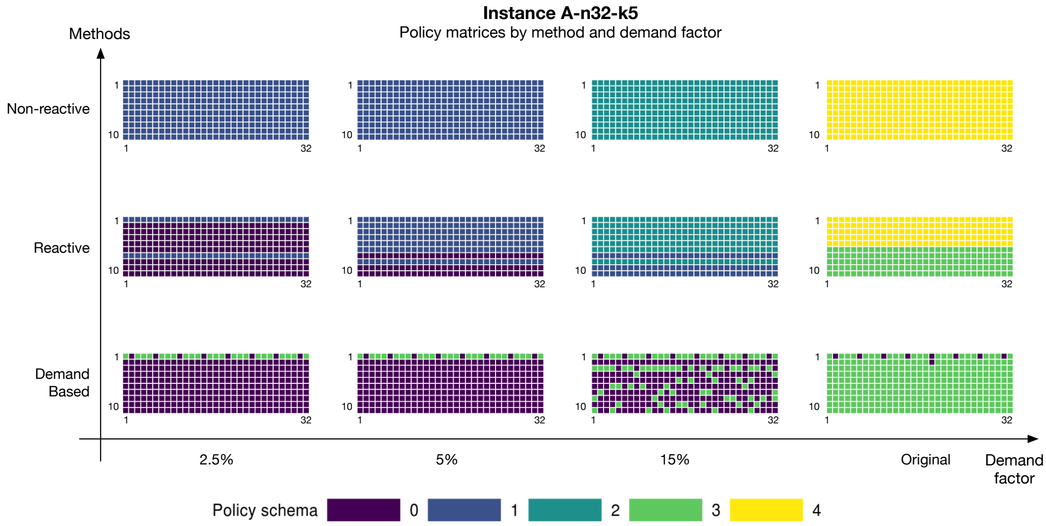



FIGURE 3.11: Selected policies according optimization method.

## 3.6 Discussion of Results and Managerial Insight

Assuming the case of animal feed distribution, one important point is that replenishment periods are typically evaluated on a daily basis. We have observed from real scenarios —for instance, animal fattening farms— where an average silo stores 6–8t, that it is commonly accepted assuming a daily consumption of 120kg–800kg of feed, which explains these low demand rates. Having this scenario in mind, it is commonly observed that the inter-period average demand scores values between 2% and 10% of the maximum capacity. Likewise, being perishable, it is considered that animal feed has a relatively high holding cost as a product distributed to the farms. Hence, scenarios with higher holding cost ($\lambda \geq 0.3$) and reduced expected demand ($\gamma \leq 15\,\%$) show the most similar behaviour to our real world case. From a strategic perspective we could state that the implementation of optimization techniques focused on feed distribution positively affects logistics costs —either the ones related to replenishment policies as well as the deliveries planning—, reducing the associated supply chain costs by 20–30 percentage points, depending on the considered demand scenario (see Figures 3.8–3.10).

Initial results show promising improvements in terms of total cost. Besides, results obtained by optimizing the whole set of available instances are consistent with previous results in the literature. We have included results obtained with $variancelevel \in \{0.25, 0.5, 0.75\}$ in Tables 3.1–3.3 using a demand factor $\gamma = 0.05$ (average expected demand is 5% of the maximum capacity. The results obtained in this scenario with the reactive method outperform the non-reactive method for every analyzed scenario of number of periods or inventory costs ($\lambda$). See Figures 3.8– 3.10 for a method comparison in terms of average total costs. As seen in Figure 3.8, for instance, by reducing the average expected demand using the demand factor, the reactive method show a positive percentage gap for every number of periods. Significant improvements arise with demand factors below 0.3 (average expected demand below 15% of the maximum stock) with both methods –reactive and demand-based approaches. Figure 3.9 shows the results obtained with a higher $lambda$ ($lambda = 0.25$). Figure 3.10 corresponds to results using $lambda = 0.5$. These results show that increasing inventory holding costs ($lambda$) do not affect the improvements obtained with both methods. However, as expected, with higher inventory holding costs the total cost is penalized when the refilling policy barely meets the expected demand –in that case, additional trips are needed to fulfill the demand.

## 3.7 Conclusions

This Chapter presents a reactive approach for the multi-period and stochastic inventory routing problem. Our approach, which is based on the combination of a biased-randomized algorithm with Monte Carlo simulation, allows for using sensors to obtain updated data on customers' demands at the end of each period. Based on this updated information, the supplier can re-optimize the distribution process for the remaining periods. Our methodology aims to determine and quantify if the use of real stock data might improve the optimization results obtained by other existing approaches in the literature, which do not consider this reactive behaviour.

Our experiments compare a static approach with two dynamic methodologies: one reactive and one based on the expected demand. The experimental results show that, in general, the availability of real-time data of inventory stocks improves the performance of the supply chain. More precisely, our reactive approach is able to outperform both the non-reactive scenario and the demand-based one. The optimization of refilling policies might have a great impact not only in distribution costs but also on in-farm availability, customer service levels, and safety stock levels.

This Chapter opens up a wide range of possibilities for research. The first step is to test the developed methodology in a real-life case study that will allow us to set relevant key performance indicators to quantify logistics cost reduction when optimizing animal feed distribution logistics. It will also allow us to establish the benefits of adopting vendor-managed inventories strategies by implementing remote stock monitoring on farm bins. The next Chapter elaborates on a real case presented by the partner Grup Batallé. Its business activities span the production of pigs of high genetic value and cured hams. Presents a real scenario to optimize their feed deliveries to farm.

# Chapter 4

# Delivering the Right Quantity to the Proper Place

> The problem today is not lack of proper resources, but lack of proper distribution.
>
> Mahatma Gandhi

## 4.1 Introduction

As the global human population grows and logistics activities become more necessary than ever, livestock production (pork, poultry, beef, etc.) is expected to raise as well. However, satisfying increasing and changing demands for animal-source foods requires a further shift from extensive- to intensive-scale operations. This intensification means a progressive introduction of industrially manufactured compound foods for the livestock sector. Commercial animal-feed companies are best placed to provide such formulated food, but there is a strong pressure to optimize the use of resources while providing the lowest cost of production to the farmer. Compound animal-food production is a global growing industry, with one billion tones produced annually that account for about $400 billion (IFIF, 2019). The European Union is the third largest animal-food producer in the world (15% share), along with USA (16%) and China (17%) (IFIF, 2019). By 2030, animal-food production is predicted to double due to the increasing mechanization and meat consumption in emerging economies (The Food and Agriculture Organization (FAO), 2019; The European Commission, 2018).

A flexible heuristic, which enriches the traditional savings heuristic (Clarke and Wright, 1964) is proposed. Apart from the multi-product, multi-compartment, and multi-day VRP, the enriched heuristic has to be able to deal with an objective function that relies on a flat-rate policy instead of on the traditional distance-based minimization. Then, this enriched savings-based heuristic is extended into a biased-randomized algorithm (BRA), which is able to provide multiple solution configurations in short computational times. As described in Grasas, Juan, Faulin, De Armas, and Ramalhinho (2017), biased-randomized techniques are based on the introduction of an oriented (non-uniform) randomization process inside the constructive stage of a given heuristic. By doing so, a deterministic heuristic is transformed into a randomized algorithm that can be run multiple times (either in sequential or in parallel) without losing the logic behind the heuristic. Hence, the main contributions of the paper can be stated as follows: *(i)* the consideration of a flat-rate cost function, together with multi-product and multi-compartment characteristics; *(ii)* the design of a flexible and fast heuristic, which enriches the traditional savings heuristic, to solve a rich and real-life problem in the agri-food distribution industry; *(iii)* the extension of the former heuristic into a biased-randomized algorithm capable of providing, in short computational times, a set of alternative solution configurations to the problem, each of these including different dimensions; and *(iv)* a numerical analysis of the proposed methodology, which allows to compare it with the costs provided by the actual firm. This Chapter discusses the case of a pork production company in Spain. We only address the part of the supply chain that distributes the food to the pigs, i.e., our work consists in designing a set of vehicle routes that meet the feed demand of a set of pigs farms. In particular, the analyzed problem can be considered a rich vehicle routing problem (VRP) (Caceres-Cruz, Arias, Guimarans, Riera, and Juan, 2014), since: *(i)* vehicles have multiple compartments to separate different types of multiple and incompatible products; *(ii)* customers may generate multiple orders in the same planning horizon; *(iii)* both variable and fixed costs are considered; and *(iv)* multiple key performance indicators (KPIs) are yielded, even when our main goal is to minimize total delivery cost.

Section 4.2 outlines the considered problem and provides details on the case study. Section 4.3 reviews the related work found in the literature. Sections 4.4 and 4.5 describe the methodology used to tackle the problem. Section 4.6 shows and discusses the main found results. Finally, Section 4.7 highlights the main contributions of this work and future research opportunities.

## 4.2 Problem Description

Feeding pigs in the pork production industry is a highly relevant activity to achieve successfully the agri-food goals. Such activity requires a precise logistics from the production plant to the farms where the pigs are raised. The part of the supply chain addressed in this Chapter is that in charge of distributing the animal food from a central depot to the farms, as displayed in Figure 4.1.

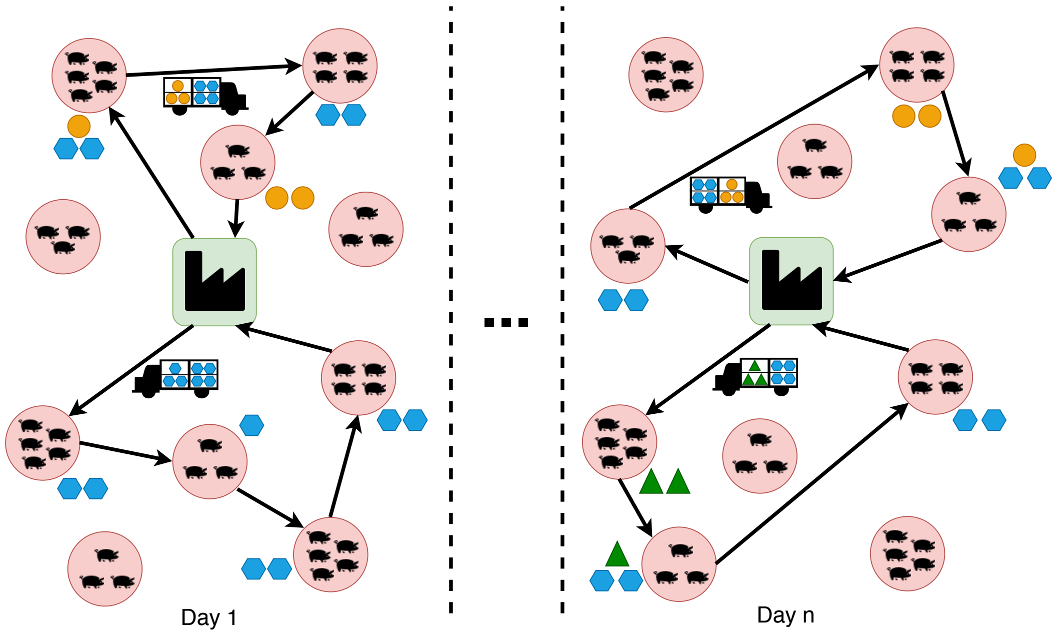



FIGURE 4.1: Representation of our real-life problem.

In our VRP, a set of farms (customers) order multiple types of feed products (represented as circles, triangles, and hexagons in Figure 4.1). These are delivered from a single depot using a fleet of homogeneous vehicles with multiple compartments (See Table 4.1 for a detailed description). The capacity of each compartment is known and fixed, although each order can easily be split into independent compartments in the same vehicle. However, different products cannot be mixed in a single compartment since they are incompatible. For each product and farm, the quantity ordered is less than the capacity of each vehicle. Therefore, orders from several customers can be loaded into the same vehicle on delivery routes, as long as the total capacity of the vehicle is not exceeded. Besides, our problem considers that any customer can make multiple orders, in different days, during a planning horizon. For instance, if the planning horizon is one week, a customer could generate two orders within two different days (Figure 4.1). Some customers might also require different products to be delivered together in the same order. Finally, the unload time at the customer's site is not considered, and all compartments are emptied at the end of each working day.

| | C1 | C2 | C3 | C4 | C5 | C6 |
|---|---|---|---|---|---|---|
| mean | 6.84 | 7.14 | 7.16 | 7.17 | 7.09 | 6.28 |
| std | 0.73 | 0.54 | 0.55 | 0.56 | 0.55 | 0.81 |
| min | 6.00 | 6.30 | 6.30 | 6.30 | 6.30 | 4.80 |
| 25% | 6.03 | 6.60 | 6.60 | 6.60 | 6.60 | 5.50 |
| 50% | 7.30 | 7.60 | 7.60 | 7.60 | 7.20 | 6.80 |
| 75% | 7.50 | 7.60 | 7.60 | 7.60 | 7.60 | 7.00 |
| max | 7.60 | 7.70 | 7.70 | 7.80 | 7.70 | 7.20 |

TABLE 4.1: Fleet capacity distribution of compartmented vehicles (18 trucks). C1-C6 columns show available capacities ($m^3$) for each compartment.

The main objective of this problem is to minimize the total delivery cost, formed by both a variable cost and a fixed cost. At the same time, all customers' demands need to be met, and constraints on the classification of different products in isolated compartments must be respected. Due to distribution agreements, the company calculates the variable cost as described next. Two tariffs are assigned to each customer: a first one, $c_s$, is applied when the delivery is made in a single round-trip without visiting any other customer. The second tariff, $c_m$, is used when the customer is part of a longer route (multiple trip). For all cases, $c_s < c_m$. These tariff assignments depend on the zone where each customer is located. For instance, a customer in a given zone has a delivery tariff of $c_s = 8.50$ €$/t$ when it is the only node in the route, whereas the same customer has a tariff of $c_m = 8.67$ €$/t$ if it belongs to a route in which other customers are also visited. See the example in Figure 4.2, where the square represents the depot and the circles are customers. These are served either in separated routes (Figure 4.2a) or as a part of a single route (Figure 4.2b). The total demand satisfied is the same in both cases, and the costs depend on the supplied food-load in tonnes. Therefore, the case in Figure 4.2b incurs in a higher variable cost than the example in Figure 4.2a. Notice that variable costs are computed differently than in most VRP articles, which is due to the existence of a flat-rate agreement between the food manufacturer and the food distributor. Besides, the consideration of this policy implies that merging routes according to the traditional savings heuristic yields to higher variable costs. Hence, the approach used to solve this VRP must be adapted to the specific characteristics of the real-life cost function.

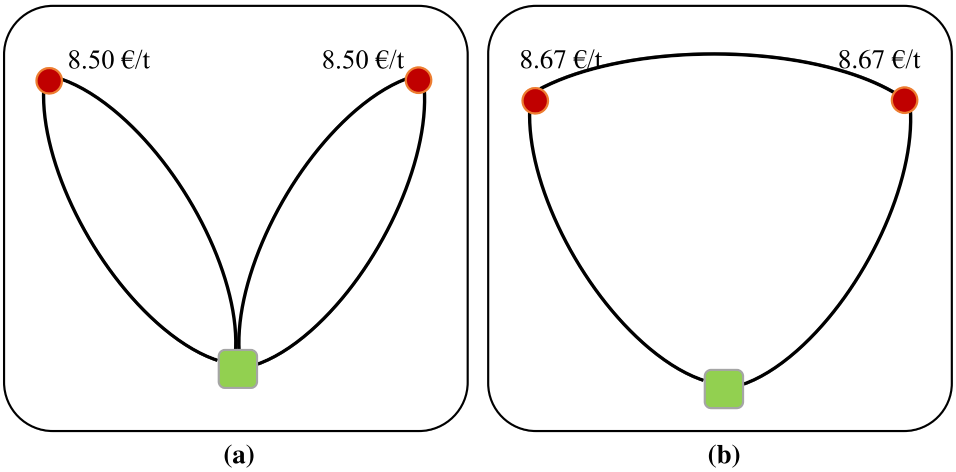



FIGURE 4.2: Example of tariffs used by the company.

The fixed cost is computed as a function of: *(i)* the number of routes; and *(ii)* a unitary fixed cost per route or vehicle, $\lambda$. This parameter is usually considered in real-world cases, but barely addressed in both the traditional VRP and the multi-compartment VRP. Previous works addressing fixed costs consider either a heterogeneous fleet (Coelho, Grasas, Ramalhinho, Coelho, Souza, and Cruz, 2016; Juan, Faulin, Caceres-Cruz, Barrios, and Martinez, 2014; Prins, 2009; Wassan and Osman, 2002) or a homogeneous fleet (Bhusiri, Qureshi, and Taniguchi, 2014; Côté and Potvin, 2009). For instance, suppose that the total demand in Figure 4.2 is 8 $t$. If $\lambda = 0$, the total delivery cost is $C = 8.50 \cdot 8 = 68.00$ € for the separated routes in Figure 4.2a. However, for the single-route (Figure 4.2b), the total cost is $C = 8.67 \cdot 8 = 69.36$ € . In contrast, if the unit fixed cost is $\lambda = 10$ per route, the total delivery costs is $C = 10 \cdot 2 + 8.50 \cdot 8 = 88.00$ € for the case in Figure 4.2a, and $C = 10 \cdot 1 + 8.67 \cdot 8 = 79.36$ € for the case in Figure 4.2b. These examples show the relevance of considering fixed costs, since the best-found solution depends on their value. Hence, when such delivery tariffs are considered, variable costs increase after merging routes, and fixed costs decrease due to the reduction in the number of routes.

The considered problem requires that the total delivery cost is not the only key performance indicator (KPI), i.e., the approach used to solve this problem must show enough flexibility to consider the following KPIs: number of designed routes, average utilization of vehicles, and other indicators considered suitable by the company. Despite its non-typical objective function, the problem can be classified as a multi-product, multi-compartment, and multi-order VRP. Hence, it is an *NP-hard* problem and, as such, the use of column-generation approaches (Taş, 2020) or heuristic-based approaches is justified whenever the size of the problem goes beyond a certain level.

## 4.3 Literature Review

Rich vehicle routing problems have been increasingly addressed by the academic community, since they incorporate highly realistic constraints, especially when these are considered simultaneously (Azadeh and Farrokhi-Asl, 2019). Characteristics regarding input data, decision management components, vehicles, time constraints, among others, turns a classical VRP into a rich VRP (Lahyani, Khemakhem, and Semet, 2015). For instance, Alemany, Armas, Juan, García-Sánchez, García-Meizoso, and Ortega-Mier (2016) combine the well-known savings heuristic (Clarke and Wright, 1964) with Monte Carlo simulation to solve a heterogeneous-fleet, multi-depot, multi-compartment, multi-product, and multi-trip VRP. The algorithm consists in: *(i)* generating a mapping of customer-to-depot assignments; *(ii)* generating a routing plan for each depot-customers set; and *(iii)* enhancing each route through a *2-opt* local search. Stages *(i)* and *(ii)* make use of a biased-randomized procedure that finds better solutions in terms of costs, and a real-life case is considered to evaluate the performance of their approach.

### 4.3.1 The Multi-Compartment VRP

Regarding physical characteristics of vehicles, these can be homogeneous or heterogeneous, fixed or unlimited, and compartmentalized or not. The multi-compartment VRP is still a rarely studied field (Derigs, Gottlieb, Kalkoff, Piesche, Rothlauf, and Vogel, 2011). Its relevance arise from real-world cases in which a set of incompatible products must be delivered to a set of heterogeneous customers, i.e., each customer demands a subset of different products. Such incompatibility forces that products must not be mixed. An alternative to avoid mixing is transporting each product into a dedicated vehicle. However, this strategy complicates the design of routes to serve customers using the same vehicle, increasing distribution costs. Therefore, the most used strategy is to have compartmentalized vehicles, so that different products are carried separately into the same vehicle.

Both theoretical and real-world cases can be found in the multi-compartment VRP literature. Works by Silvestrin and Ritt (2017), Muyldermans and Pang (2010), and El Fallahi, Prins, and Calvo (2008) are examples of the former. All these authors propose metaheuristic approaches given the combinatorial nature of this problem. They also consider a deterministic version of the multi-compartment VRP. In contrast, works by Mendoza, Castanier, Guéret, Medaglia, and Velasco (2011) and Mendoza, Castanier, Guéret, Medaglia, and Velasco (2010) consider stochastic demands. Dynamic programming approaches to solve this problem are also found in the literature, e.g., Pandelis, Kyriakidis, and Dimitrakos (2012), Tatarakis and Minis (2009), and Tsirimpas, Tatarakis, Minis, and Kyriakidis (2008). Problems arisen from waste collection activities and apparel, fuel, and food industries motivate the research applied to real-world cases (Wang, Ji, and Chiu, 2014). For instance, multi-compartment vehicles are necessary in waste collection to separate properly the different types of recycling waste (Reed, Yiannakou, and Evering, 2014). Multiple compartments are also mandatory to transport multiple petroleum products in the fuel distribution problem (Coelho and Laporte, 2015). Including inventory decisions in routing is usual in these cases (Vidović, Popović, and Ratković, 2014; Popović, Vidović, and Radivojević, 2012). Multi-compartment real-life cases can also be found in Derigs, Gottlieb, Kalkoff, Piesche, Rothlauf, and Vogel (2011). They propose a solver suite combining different heuristics and metaheuristics to solve this problem. Petrol and food industries are presented as typical realistic examples where compartmentalized vehicles are necessary. Specific characteristics of these industries are considered to create 200 instances for the multi-compartment VRP. Comparisons with other algorithms from the literature are carried out, and the obtained quality of results are higher for most instances. Finally, these authors find that the difference in inputs from each considered industry does not affect the algorithm results. Abdulkader, Gajpal, and Elmekkawy (2015) combine an ant colony algorithm with local search schemes to solve a multi-compartment VRP. The proposed algorithm is compared with traditional ant colony approaches. Besides, these authors compare the effect of considering two-compartment vehicles instead of single-compartment ones in waste collection. These two referred works state that food vehicles usually have two compartments: one for transporting refrigerated products and another one for ambient products.

### 4.3.2 Multi-Compartment VRPs in Agri-Food Supply Chains

An agri-food supply chain has special characteristics that must be taken into account in its modelling, such as products perishability (Tordecilla-Madera, Polo, and Cañón, 2018) or supply and demand seasonality (Vlajic, Vorst, and Haijema, 2012). Considering specifically agri-food multi-compartment VRPs, works using either exact or approximate methods can be found. Regarding the former, Lahyani, Coelho, Khemakhem, Laporte, and Semet (2015) propose a branch-and-cut algorithm to solve a multi-period and multi-compartment VRP with heterogeneous vehicles. A real case from the olive-oil collection process in Tunisia is considered. Three grades of olive oil are transported, from superior to inferior quality. A compartment transporting the lowest-grade oil must be cleaned after being used, thus incurring additional costs and time –unless the same grade oil is loaded there. The cleaning activity has been barely addressed by the literature. Oppen, Løkketangen, and Desrosiers (2010) address also cleaning activities in an multi-compartment VRP with inventory constraints. They solve the so-called *livestock collection problem* through an exact solution method based on column generation. Animals from different types and categories are transported, and they cannot be mixed in the same compartment. Heterogeneous fleet and multiple trips are considered. Instances up to 27 orders are solved in reasonable computational times by employing their approach. Using approximate methods is a usual approach in agri-food multi-compartment VRPs. For instance, Caramia and Guerriero (2010) propose a hybrid approach combining mathematical programming and local search techniques to solve a real-life case regarding the collection of different types of milk in Italy. This problem considers that some customers cannot be reached by a 'complete vehicle' formed by a truck and a trailer, but only by the truck. This means that collecting milk to these customers imply to uncouple the trailer, to visit one or several customers using only the truck, and to couple the trailer again. Additional costs and time are incurred to carry out these activities.

### 4.3.3 Flexible Multi-Compartment VRPs

Finally, an interesting problem arises when considering flexible compartments, i.e., the number and capacity are variable in each vehicle. For instance, Hübner and Ostermeier (2019) propose a large neighborhood search algorithm to solve this problem. A relevant contribution of their paper is the consideration of loading and unloading costs, which are a function of the number of compartments. Authors explain that different compartments are necessary given specific temperature requirements for each product preservation. A case study from the food industry is considered. Ostermeier and Hübner (2018) address a similar problem, but they also tackle decisions regarding vehicles selection, i.e.: any route may be served either by a single- or a multi-compartment vehicle. This additional variable enhances the obtained results compared to cases that consider only one type of vehicle.

## 4.4 A Flexible and Fast Heuristic

The described real-life problem shows a set of characteristics that increases its complexity, namely: *(i)* constraints regarding multiple compartments, products and orders; *(ii)* an objective function considering delivery tariffs; and *(iii)* the consideration of multiple KPIs. In order to include all these characteristics, a flexible solving approach is needed. Besides, being an *NP-hard* problem exact approaches are not able to provide 'agile' solutions as requested by the food distribution firm. Hence, a flexible and fast heuristic is proposed in this section.

Algorithm 4 provides a general view of the proposed heuristic to solve the VRP with multiple products, compartments, and orders (VRP-MPCO). Firstly, each customer requiring *multiple products* and *orders* is split into several virtual customers, who only require a single product and a single order (line 1). In other words, the heuristic creates virtual customers considering that each product and order is demanded by different clients located at the same place. Then, the algorithm computes the distance-based savings generated when merging a pair of routes by connecting a pair of nodes (line 2), i.e., a single value of savings is computed for each edge in the network. A savings list is created and sorted following a decreasing order. Next, a 'dummy' solution is generated. In it, each virtual customer is visited from the depot in a single round trip (line 3). At this point, the next element in the savings list is selected (line 5), starting with the highest-savings edge in the first iteration. The origin and destination nodes forming this edge and their evolving routes are retrieved (lines 6, 7, and 8). The edge is selected to be part of the solution only if it meets the following merging conditions (line 9): *(i)* each node in the origin and the end of the edge belongs to different routes; and *(ii)* these nodes are adjacent to the depot. Notice that the total vehicle capacity is not considered, as traditional savings heuristics do. Instead, each compartment capacity is assessed in the next step, in which the resulting demand is distributed into the *multiple compartments* of the vehicle (line 10 and Algorithm 5). When a feasible assignment is found, the algorithm merges the routes (line 11) and updates the solution by removing the routes at both extremes of the selected edge, *oRoute* and *dRoute*. The new merged route is added to the emerging solution (line 12). All KPIs and the variable cost are also updated, considering the *flat-rate delivery tariffs* (Figure 4.2). Once the nodes have been connected, the multiple-trip tariff ($c_m$) is used to calculate the variable cost: if $V$ = variable cost, and $d$ = total demand of the merged route, then $V = c_m \cdot d$. Again, notice that this approach is different to the distance-based cost computation employed in most articles on the VRP, which do not consider the flat-rate tariff. Now, the current edge is removed from the list (line 14), and the whole process is repeated until the savings list is empty. Finally, virtual customers belonging to the same farm are merged (line 16).

1: $virtualCustomers \leftarrow splitNodes(inputParameters)$
2: $savingsList \leftarrow generateSavings(virtualCustomers)$
3: $Solution \leftarrow generateDummy(virtualCustomers)$
4: **while** $savingsList$ is **not** empty **do**
5:     $e \leftarrow selectNextEdgeFromList(savingsList)$
6:     $\{oNode, dNode\} \leftarrow getNodes(e)$
7:     $oRoute \leftarrow getEvolvingRouteOfNode(oNode)$
8:     $dRoute \leftarrow getEvolvingRouteOfNode(dNode)$
9:     **if** route-merging conditions are met **then**
10:         $assign \leftarrow calcDistribution(inputParameters, oRoute, dRoute)$
11:         $newRoute \leftarrow mergeRoutes(oRoute, dRoute, assign)$
12:         $Solution \leftarrow update(Solution, newRoute)$
13:     **end if**
14:     $savingsList \leftarrow removeEdge(savingsList, pos)$
15: **end while**
16: $Solution \leftarrow mergeNodes(Solution)$
17: **return** $Solution$

**Algorithm 4:** VRPMPCO (inputParameters).

As the assignment of compartments to products has to meet the set of constraints described in Section 4.2, Algorithm 5 verifies that the aggregate demand of two possible merged routes can be loaded into the available compartments of a vehicle. Firstly, all possible permutations of the compartments are generated (line 1). Then, the first permutation of the list is selected (line 3). The demands of each product in the merging routes are added (line 5), since they all must be met. Line 10 of Algorithm 7 has already verified that this added demand is less than the total vehicle capacity. Next, each type of product is tried to be placed into each compartment of each permutation, meeting the established constraints (line 7). This procedure is repeated until a feasible assignment is found.

```
1: permutationList ← genPerm(compartmentsList)
2: repeat
3:    perm ← getFirstPermutation(permutationList)
4:    for prod ∈ productsList do
5:       dem ← getDemand(oRoute, prod) + getDemand(dRoute, prod)
6:       for comp ∈ perm do
7:          assign ← place(perm, dem, comp)
8:       end for
9:    end for
10: until assign is feasible
11: return assign
```

**Algorithm 5:** calcDistribution (inputParameters, oRoute, dRoute).

## 4.5 Extending the Heuristic to a Biased-Randomized Algorithm

Despite minimizing the total delivery cost is our main objective, other KPIs are also considered by decision makers at the food production firm –these decision makers might have different utility functions than the ones at the food distribution firm. Algorithm 4 is designed to yield only one solution. Nevertheless, a single solution is not very convenient when considering multiple KPIs and different decision makers with varying utility functions. Therefore, the previous heuristic is extended into a biased-randomized algorithm to generate multiple alternative solutions. Given the simplicity of the solution-construction process, the BRA is highly flexible and it can be easily adapted to take into account not only the characteristics and constraints of the problem already introduced, but also others that the decision makers might request in the future.

Algorithm 6 depicts the proposed approach, which returns a set of alternative 'best' solutions named *eliteSolutions*. This set contains solutions that offer the best-found value for each of the considered KPIs: distance, fixed cost (number of routes), variable cost, and average utilization of vehicles –notice that, due to the flexibility of our approach, other KPIs can be easily added if the distribution or the manufacturing firm requests them. Firstly, our approach makes use of the Algorithm 4 to yield an initial solution, which is introduced in the *eliteSolutions* set (line 2). Secondly, the main loop is executed until a maximum time is reached. For each iteration, the procedure in Algorithm 7 is called (line 4), and it returns a new solution. This new solution is compared to those already stored in *eliteSolutions* (line 5). The new solution is included here (line 6) only if it outperforms any solution in this set.

Algorithm 7 outlines the BRA stage. Broadly speaking, this approach uses a skewed probability distribution (e.g., the geometric distribution) to carry out the selection of the next element in a constructive process, i.e.: the first element in the list has the highest probability of being chosen, the second element has the second highest probability, and so on. This procedure diversifies the search by exploring other regions of the solutions space. Successful applications in areas as diverse as logistics (Estrada-Moreno, Ferrer, Juan, Bagirov,

$Solution \leftarrow VRPMPCO(inputParameters)$
$eliteSolutions \leftarrow addSolution(Solution)$
**repeat**
  $Solution \leftarrow BRA(inputParameters, \beta)$
  **if** $Solution$ is an elite solution **then**
    $eliteSolutions \leftarrow addSolution(Solution)$
  **end if**
**until** time reaches the limit
**return** $eliteSolutions$

**Algorithm 6:** General(inputParameters, $\beta$).

and Panadero, 2019; Quintero-Araujo, Caballero-Villalobos, Juan, and Montoya-Torres, 2017; Armas, Juan, Marquès, and Pedroso, 2017), transportation (Belloso, Juan, and Faulin, 2019; Dominguez, Juan, Nuez, and Ouelhadj, 2016), scheduling (Ferone, Hatami, González-Neira, Juan, and Festa, 2020; Ferrer, Guimarans, Ramalhinho, and Juan, 2016; Gonzalez-Neira, Ferone, Hatami, and Juan, 2017), finance (Panadero, Doering, Kizys, Juan, and Fito, 2020), or mobile cloud computing (Mazza, Pages-Bernaus, Tarchi, Juan, and Corazza, 2016) have demonstrated the efficiency of biased-randomization techniques, which can also be used to enhance existing metaheuristic frameworks (Ferone, Gruler, Festa, and Juan, 2019). As our proposed heuristic in Algorithm 4 is the base of our BRA, Algorithm 7 contains almost the same steps, except for lines 5 and 6. Here, a random position ($pos$) is generated according to a geometric probability distribution with parameter $0 < \beta < 1$. This parameter indicates the probability of selecting the most promising element in the savings list. Then, an edge $e$ is selected according to $pos$, instead of the first element chosen in the non-randomized heuristic. After the remaining steps are executed, a different solution is obtained each time the algorithm is run, which provides the probabilistic nature to the algorithm.

1: $virtualCustomers \leftarrow splitNodes(inputParameters)$
2: $savingsList \leftarrow generateSavings(virtualCustomers)$
3: $Solution \leftarrow generateDummy(virtualCustomers)$
4: **while** $savingsList$ is **not** empty **do**
5:   Randomly select position $pos \in \{1, ..., savingsList\}$ according to Geom($\beta$) distrib.
6:   $e \leftarrow selectEdgeFromList(pos, savingsList)$
7:   $\{oNode, dNode\} \leftarrow getNodes(e)$
8:   $oRoute \leftarrow getEvolvingRouteOfNode(oNode)$
9:   $dRoute \leftarrow getEvolvingRouteOfNode(dNode)$
10:   **if** route-merging conditions are met **then**
11:     $assign \leftarrow calcDistribution(inputParameters, oRoute, dRoute)$
12:     $newRoute \leftarrow mergeRoutes(oRoute, dRoute, assign)$
13:     $Solution \leftarrow update(Solution, newRoute)$
14:   **end if**
15:   $savingsList \leftarrow removeEdge(savingsList, pos)$
16: **end while**
17: $Solution \leftarrow mergeNodes(Solution)$
18: **return** $Solution$

**Algorithm 7:** BRA (inputParameters, $\beta$).

## 4.6 Computational Experiments

Real-world instances have been provided by the firm. They represent daily deliveries made to 192 customers in a period of 5 months. The firm's planning horizon for deliveries is one week, which are done only in working days (Monday to Friday). Currently, the firm delivers just when the customer generates an order. For that reason, only a subset of these customers is served in this period. On the average, 147 customers are served per week. The feed shelf life is greater than one week. Therefore, perishability is not included in our case study. Each customer may require several types of food at the same time. Each week represents an instance in our experiments, and 21 instances were built in total. The firm's vehicles have 6 compartments with a capacity of 4.48 $t$ each. A number of different products are supplied. Therefore, they are aggregated to form a quantity of 26 animal-food families.

The geometric probability distribution is used to introduce the biased-randomization in the heuristic-constructive process. It has only one parameter to be fine-tuned ($\beta$). In our experiments, $\beta$ is not fixed with a single value, but it varies in an interval between a minimum and a maximum values. After some quick tests, we decided to select the range $\beta \in (0.2, 0.4)$. A maximum time of 120 seconds is established to perform the biased-randomization process. All experiments were run in a PC with an $i7-8750$H at 2.2 GHz processor and 16 GB RAM.

### 4.6.1 Results Obtained with Our Approach

Our main results are expressed in terms of the traveled distance, variable and fixed costs, the average utilization of vehicles, the number of iterations made by the biased-randomized algorithm, and the time in which our best solution (OBS) was found. Since the fixed cost depends on $\lambda$ (the unit fixed cost per route or vehicle), the total delivery cost is also a function of this parameter. That is, if $V =$ variable cost, $R =$ number of routes, and $C =$ total cost, the latter is computed as $C(\lambda) = R \cdot \lambda + V$. Real-world data from the company and our results are displayed and compared in Table 4.2. The number of nodes and the total required and met demand per instance are also shown. The data corresponding to the company represents the real plans executed to supply the feed. This table displays different solutions yielded by our algorithm: a 'dummy' solution, in which each customer is visited separately, and the best solution obtained by our biased-randomized algorithm. Since our biased-randomized algorithm promotes the merging between routes –as far as this merge does not violate any constraint–, costs in column (10) are always smaller than costs in column (7). In turn, both are always smaller than costs in column (4). As expected, variable costs are higher after merging the routes, given the use of delivery tariffs. In contrast, the number of routes yielded by the heuristic and the biased-randomized algorithms are always smaller than the ones obtained by the dummy solution.

TABLE 4.2: Results comparison between our approach and the real-world plans.

| Instance | # Nodes | Demand (t/week) | Company results | | Dummy solution | | Our non-randomized heuristic | | | BRA | | | | | | Gap | Gap |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Fixed cost (#Routes) (1) | Variable Cost (2) | Variable Cost (3) | Distance (4) | Fixed cost (#Routes) (5) | Variable Cost (6) | Distance (7) | Fixed cost (#Routes) (8) | Variable Cost (9) | Distance (OBS) (10) | Average utilization of vehicles (11) | Total Iterations (12) | OBS Time (s) (13) | (1)-(8) | (2)-(9) |
| 1 | 128 | 1643.7 | 75λ | 13217 | 12871 | 4993 | 73λ | 13173 | 3105 | 71λ | 13274 | 3024 | 86.1% | 107 | 28.88 | -5.33% | 0.43% |
| 2 | 218 | 2614.5 | 114λ | 20920 | 20139 | 8236 | 115λ | 20665 | 4886 | 113λ | 20662 | 4808 | 86.1% | 42 | 2.41 | -0.88% | -1.23% |
| 3 | 205 | 2256.0 | 101λ | 17917 | 17145 | 7280 | 98λ | 17707 | 4064 | 96λ | 17741 | 4022 | 87.4% | 51 | 41.46 | -4.95% | -0.98% |
| 4 | 209 | 2385.9 | 107λ | 18938 | 18251 | 7829 | 104λ | 18751 | 4487 | 105λ | 18749 | 4349 | 84.5% | 47 | 112.76 | -1.87% | -1.00% |
| 5 | 220 | 2376.6 | 107λ | 19228 | 18418 | 7669 | 104λ | 18832 | 4292 | 104λ | 18818 | 4270 | 85.0% | 45 | 80.53 | -2.80% | -2.13% |
| 6 | 209 | 2435.6 | 108λ | 19289 | 18635 | 7702 | 105λ | 19131 | 4417 | 105λ | 19118 | 4274 | 86.3% | 48 | 85.39 | -2.78% | -0.89% |
| 7 | 205 | 2464.4 | 107λ | 19477 | 18749 | 7298 | 110λ | 19135 | 4335 | 107λ | 19242 | 4317 | 85.7% | 46 | 34.11 | 0.00% | -1.21% |
| 8 | 183 | 2012.8 | 91λ | 15991 | 15433 | 6726 | 87λ | 15868 | 3636 | 86λ | 15889 | 3544 | 87.1% | 66 | 67.11 | -5.49% | -0.64% |
| 9 | 204 | 2408.3 | 106λ | 19209 | 18474 | 7425 | 105λ | 18957 | 4428 | 105λ | 18980 | 4262 | 85.3% | 51 | 94.13 | -0.94% | -1.19% |
| 10 | 198 | 2258.6 | 101λ | 17559 | 17034 | 7217 | 98λ | 17384 | 3899 | 97λ | 17461 | 3799 | 86.6% | 56 | 57.48 | -3.96% | -0.56% |
| 11 | 212 | 2403.6 | 106λ | 18860 | 18398 | 7852 | 103λ | 18871 | 4357 | 104λ | 18829 | 4251 | 86.0% | 50 | 24.99 | -1.89% | -0.16% |
| 12 | 195 | 2167.6 | 97λ | 17028 | 16461 | 7115 | 94λ | 16817 | 3836 | 93λ | 16840 | 3767 | 86.7% | 57 | 42.86 | -4.12% | -1.10% |
| 13 | 180 | 2310.4 | 101λ | 18089 | 17542 | 6545 | 100λ | 17824 | 3970 | 100λ | 17830 | 3917 | 86.0% | 59 | 62.65 | -0.99% | -1.43% |
| 14 | 207 | 2245.1 | 98λ | 17698 | 16851 | 7186 | 95λ | 17570 | 3874 | 94λ | 17597 | 3800 | 88.9% | 56 | 89.97 | -4.08% | -0.57% |
| 15 | 216 | 2576.4 | 115λ | 20077 | 19537 | 7788 | 111λ | 20036 | 4583 | 110λ | 20021 | 4422 | 87.1% | 45 | 3.15 | -4.35% | -0.28% |
| 16 | 212 | 2526.7 | 112λ | 19692 | 19107 | 7649 | 108λ | 19638 | 4343 | 108λ | 19698 | 4292 | 87.0% | 47 | 110.30 | -3.57% | 0.03% |
| 17 | 197 | 2415.5 | 106λ | 19119 | 18598 | 7442 | 103λ | 19019 | 4311 | 103λ | 19056 | 4270 | 87.3% | 51 | 119.74 | -2.83% | -0.33% |
| 18 | 219 | 2432.1 | 106λ | 19013 | 18387 | 7649 | 103λ | 18895 | 4059 | 102λ | 18943 | 4007 | 88.7% | 47 | 8.16 | -3.77% | -0.37% |
| 19 | 208 | 2445.9 | 108λ | 18956 | 18405 | 7305 | 106λ | 18891 | 4163 | 108λ | 18842 | 4151 | 84.3% | 47 | 98.63 | 0.00% | -0.60% |
| 20 | 217 | 2530.5 | 113λ | 19524 | 19122 | 7759 | 112λ | 19425 | 4524 | 112λ | 19418 | 4417 | 84.1% | 43 | 62.46 | -0.88% | -0.54% |
| 21 | 239 | 2584.8 | 114λ | 20672 | 20015 | 8790 | 114λ | 20458 | 4660 | 113λ | 20456 | 4648 | 85.1% | 39 | 6.40 | -0.88% | -1.04% |
| **Total** | | 49495.0 | 2193λ | 390473 | 377572 | 155455 | 2148λ | 387047 | 88229 | 2136λ | 387464 | 86611 | | | | | |
| **Average** | 204 | 2356.9 | 104λ | 18594 | 17980 | 7403 | 102λ | 18431 | 4201 | 102λ | 18451 | 4124 | 86.2% | 52 | 58.74 | -2.68% | -0.75% |

The gaps between our algorithm and the real plans by the firm are also shown in Table 4.2. Even in terms of variable costs –i.e., without considering fixed costs– our results are better for most instances. In addition, our solutions always use less (or equal) number of routes than ones employed by the firm, which means lower fixed costs. In particular, our solutions employ less routes than the firm's solution in 19-out-of-21 instances. A reduction up to 5.49% is attained, and the average reduction is 2.68% per week. Regarding variable costs of delivery, a slight reduction is obtained also in 19-out-of-21 instances. The average variable cost reduction is 0.75% –without considering the reduction in fixed costs, which is significantly higher. These results demonstrate two main advantages of our approach: *(i)* our algorithm outperforms the firm's results in variable costs for most instances; and *(ii)* our algorithm has been validated as a faithful representation of the system under study, since our results are similar to those obtained by the company, e.g., the absolute value of the variable cost gap between the biased-randomized algorithm and the firm is never higher than 2.13% for a single instance. However, the great difference between both approaches lies in the fixed costs (i.e., number of routes), in the number of alternative solutions that our algorithm can generate, and in the savings in working hours that our algorithm provides: while the firm invests several man-hours of work per week to design the routes by hand, our approach designs them automatically in a few seconds. Besides, our algorithm is fast enough to redesign routes very quickly if unforeseen changes in customers' demands occur during the week. For instance, columns (12) and (13) show the total iterations performed in 120 seconds and the time in which the biased-randomized algorithm finds the best solution, respectively. This data shows the agility of our approach, considering the big number of nodes per instance.

An example of the design of a set of routes for a given week is shown in Figure 4.3. The algorithm's results for instance 12 indicate that 93 routes could have been designed during that week, instead of the 97 that the firm actually scheduled. To avoid overlapping of routes, the map only shows four of them. As the distance is kept as the merging criterion instead of the variable cost, almost every customer is merged with relatively close neighbors. However, the algorithm just merge a few dummy routes in a single one given the vehicles' limited capacity. Notice in column 11 of Table 4.2 that the average utilization of vehicles is 86.2%, with a minimum value of 84.1% and a maximum value of 88.9%. This means that, in general, the vehicles' utilization is high –which makes it difficult to merge more routes using the current fleet.

Figure 4.4 depicts an example in which the total cost provided by the firm is compared with the one provided by our BRA for different values of $\lambda$. It shows that our solution always outperforms the one provided by the enterprise (negative gaps), and that this improvement increases as the unitary cost per route ($\lambda$) is augmented. Hence, for $\lambda = 200$, our approach outperforms the firm's current practice by 1.8% on the average, while for $\lambda = 800$ the average improvement grows up to 2.3%. These results are noteworthy, specially considering that the BRA just needs to be run during a few seconds in standard PC, while the solution provided by the firm requires many hours of manual planning.

### 4.6.2 Solution Performance Using Other KPIs

One of the most relevant advantages of our approach is the capability of generating different alternative solutions, all of them with a reasonably good quality, in just a few seconds. Having several good alternative plans is useful for decision makers, since they can select the more convenient one according to their utility function and the characteristics of each week. Algorithm 6 stores in memory selected solutions in terms of several KPIs: traveled distance, number of routes, variable cost, and average utilization of vehicles


FIGURE 4.3: Routes designed by the BRA heuristic for the instance 12.

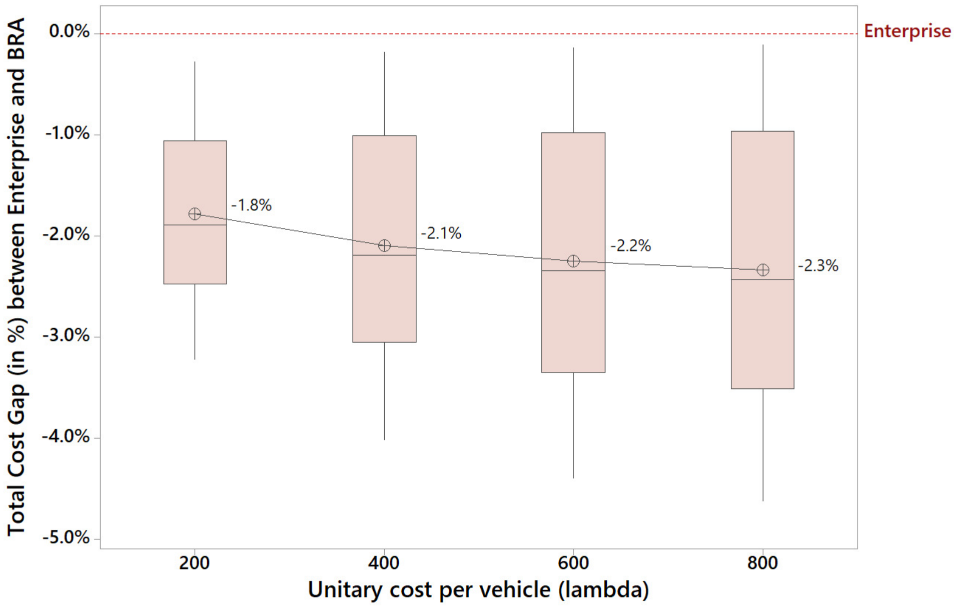



FIGURE 4.4: Total cost gap between the firm and our solution for different values of $\lambda$.

(AUCV). Figure 4.5 shows an example where three different solutions of instance 6 are depicted. For instance, the dashed orange polygon represents the best solution in terms of distance, the dash-dotted green polygon represents the best one in terms of variable cost, and the solid blue polygon is the best one in terms of number of routes and AUCV.

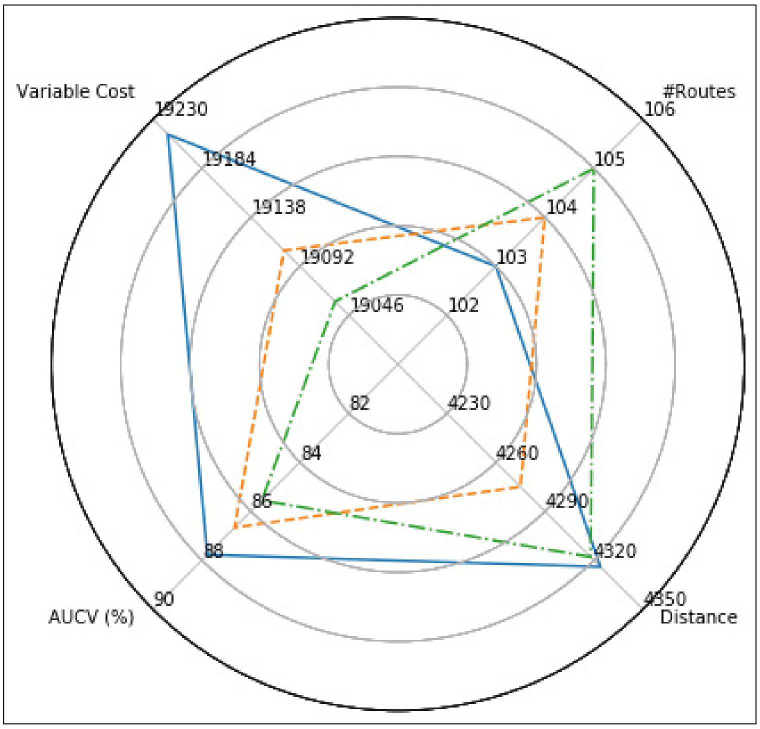



FIGURE 4.5: Three solutions for the instance 6.

## 4.7 Conclusions

In this Chapter we have proposed a flexible, savings-based, heuristic to solve a rich and real-life vehicle routing problem (VRP) in the agri-food industry. The considered VRP includes a multi-product, multi-compartment, multi-order delivery process in which the firm's costs are not just distance-based –as it is traditionally the case in the literature– but driven by a flat-rate agreement between the firm and the distributor. The constructive heuristic has then been extended into a biased-randomized algorithm in order to quickly generate a set of alternative good solutions from which the decision maker can choose.

Our algorithm is able to save the firm many hours of work in designing the routing plan, while at the same time it is able to provide solutions that outperform in total cost the ones initially proposed by the firm. The objective of our approach is to minimize the total delivery cost in a planning horizon of one week. In order to do so, we have considered the special cost structure of the firm, which makes use of a flat-rate tariff –hence, not always reducing driving distance leads necessarily to a better solution in terms of variable costs. Total costs are expressed as a function of a parameter $\lambda$, which measures the unit fixed cost per requested vehicle.

Next Chapter includes the consideration of inventory planning jointly with the vehicle routing, since farmers manage currently their own food inventory, making an order according to their daily needs. A vendor managed inventory strategy could decrease total costs. Hence, a digital twin based framework is proposed.

# Chapter 5

# Building a Digital Twin for Decision Making

One Ring to rule them all, One Ring to find them, One Ring to bring them all and in the darkness bind them.

J.R.R. Tolkien, The Lord of the Rings

## 5.1 Introduction

Agriculture is undergoing a process of vertical integration with allied industries. One of the worldwide ways of vertical integration in agriculture is contract farming (Rehber, 1998). Contract farming seeks to benefit both producers/growers and integrators. By signing a contract with a large firm, farmers can reap the benefits of a firm's enormous wealth. The firm helps the farmer reduce costs of veterinary services, provides technical assistance and advice, encourages the adoption of state-of-the-art technologies allowing the farmer to increase output while maintaining good stewardship to the environment. Animal feed producers have also joined this vertical integration, yearning to integrate their production system with their consumers, fostering vendor-managed inventories (VMI) practices that would benefit the whole supply chain. However, main efforts to connect on-farm feeding activities with feed logistics have been unsuccessful due to the difficulties to measure the farm feed stocks accurately within affordable costs.

This Chapter summarises the work done within the IoFEED project (`https://www.iof2020.eu`), which aims to monitor approximately 325 bins and investigate business processes carried out between farmers and animal-food producers. Initially, two test-beds have been set in two distinct European countries, the United Kingdom (UK) and Spain (ES). The UK has a partner with 50 bins, while Spain has a single partner with 50 devices. After this initial phase, the number of monitored bins has increased up to 175 more for the Spanish pilot. Two business processes will be put to test in this project, which will analyze their cost-benefit and cost-effectiveness:

- *Business Process 1 (BP1)*, focused on farmers; BP1 aims to provide the best solution for farmers to achieve a seamless procedure to measure bins' stock. The goals are: to provide accurate real-time information for daily tracking of food consumption in the farm, to assess feeding costs, and to help the farmer to increase his / her feed conversion rate, including a reduction in stock ruptures.

- *Business Process 2 (BP2)*, focused on helping animal-food manufacturers. Additionally to BP1 benefits, BP2 aims to change the business strategy moving the workload balance of maintaining the food stock to the feed supplier, so they can handle and manage the correct and exact amount of food for each bin that covers their client needs (the farmer) while, at the same time, optimizing the supply chain cost (production, own stocks, product shipping / distribution, etc.).

The remainder of this Chapter is structured as follows: Section 5.2 outlines the considered problem and provides details on the case study; Section 5.3 provides the related work found in the state of the art; Section 5.4 describes the framework used to tackle the problem; Section 5.5 shows and discusses the main insights; and finally, Section 5.6 highlights the main contributions of this work and future research opportunities.

## 5.2 Stakeholders' Analysis and Needs Assessment

The two test-beds provided by the selected partners represent distinct business models with which the animal industry face the feed distribution: free market (Dugdale Nutrition, UK) and contract farming (Batallé Group). Although they could suffer from distinct pains, what they both have in common is a desire to push their animal feed distribution into the new age. In the Spanish pilot, The Batallé Group is made up of companies that work across different phases of the pork production chain. Its business activities span the breeding of high quality pigs, production of cured hams, and the marketing of cuts of meat for the global market. Batallé's feed provider is the company ESPORC. Founded in 2002 and nowadays part of the holding. In the UK pilot, Dugdale Nutrition manufactures the compound feeds at their Clitheroe site at 100% capacity. Dugdale is a family owned business which has delivered innovation in the ruminant sector for over 170 years. With two production facilities running 24/7, they manufacture in excess of $250,000$ tonnes of feed per year and have 24 dedicated vehicles out on the road delivering feed onto farm 363 days per year.

Feeding animal livestock is vital to these companies successfully achieving their goals. Figure 5.1 shows how these two pilots present distinct scenarios according to their monthly consumption. For instance, first bucked shows how the $14.7\%$ of the Spanish pilot's farms has an average monthly consumption below $10$ tonnes, while $35.1\%$ of the UK pilot's farms have this same consumption range. While the Spanish pilot focuses on farms where the main activity is pig rearing, the UK pilot deals with dairy farms. Both pilots aim to deliver fresh feed with the specific diet to farm. Such activity requires precise logistics from the feed mill to the farms. The business process involves distinct management actors such as the farm, the feed manufacturing, the sales department, and the distribution department.

The stakeholder analysis (Figure 5.2) has identified common pains mostly related with the lack of a short term demand forecasting. For instance, the UK pilot (free market) has allowed us to identify concerns with: *(i)* farms with large orders ($>$ 30Tn/month/single product), where providing on-time deliveries may be crucial; *(ii)* clients geographically spread, where urgent order may be costly to serve; *(iii)* clients that produce significant number of urgent orders; *(iv)* clients where knowing accurate stocks may shorten production lead time, and may also allow to adjust the feed production to the real demand distribution; and *(v)* improve customer loyalty by provide a better service. The Spanish partner (contract farming), has also identified the need for having the farm feed inventories under control, as well as the production plans at each production unit – as they manage not only the feed delivery but also the nutritional plans. To them, optimizing the feed supply chain means having reliable inventory stock levels to generate timely and

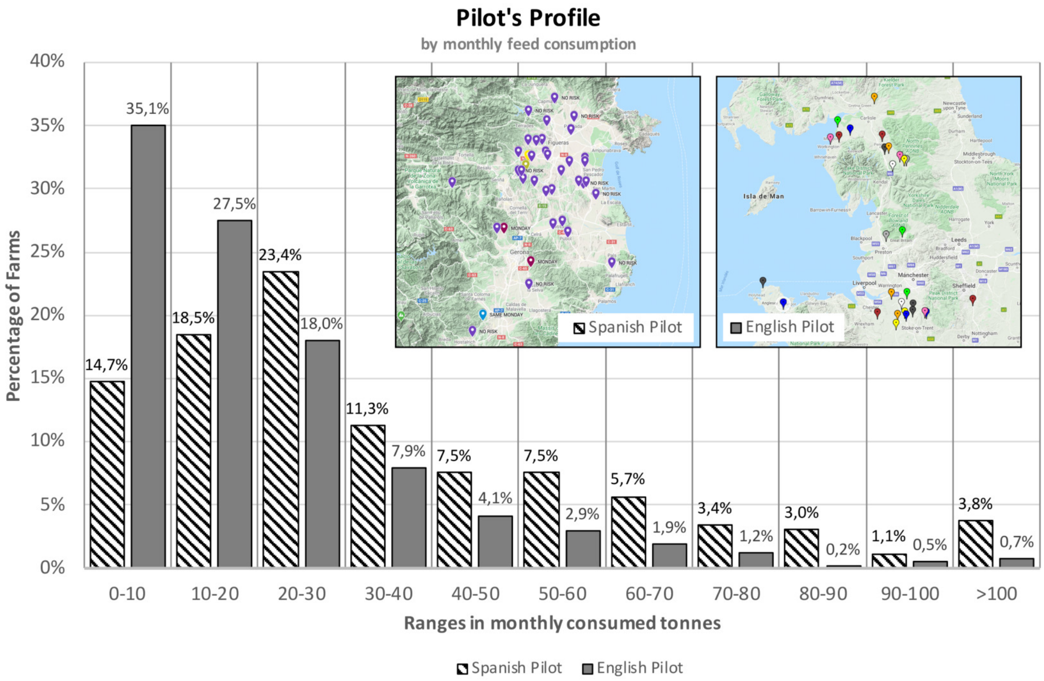



FIGURE 5.1: Farm number distribution according to monthly feed consumption.

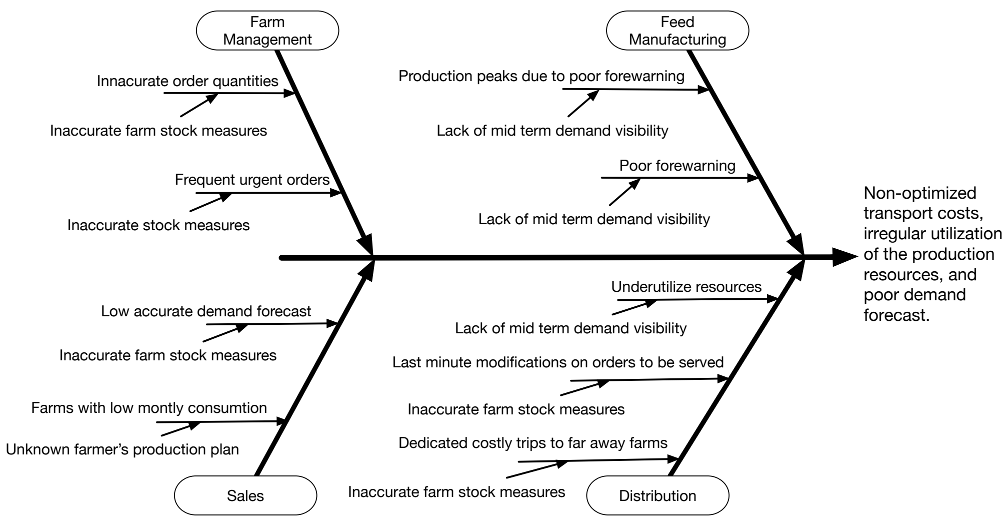



FIGURE 5.2: Consequences of inexistent or poor demand forecasting.

accurate orders. At the end, if a feed manufacturer knows accurately their feed demand, the following benefits apply: *(i)* urgent orders produced by unexpected stock outs will be reduced; *(ii)* the production curve will be smooth by forewarning the products and quantities to produce; and *(iii)* service routing will be planned ahead without unexpected services and unplanned peaks. Essentially, knowing their clients' stock levels will allow them to increase their delivery performance, reduce transport costs, and improve the utilization of their production resources.

### 5.2.1 Business Problem

Our main goal consists in automating and optimizing the logistics of animal feed distribution over a given set of farms. Orders can be of multiple types of feed products (represented as geometrical shapes in Figure 5.3). These orders are shipped from multiple depots by using a fleet of heterogeneous vehicles with multiple compartments. The capacity of each compartment is known and fixed, although each order can easily be split into independent compartments in the same vehicle – without mixing distinct products in a single compartment. The total quantity of product ordered by each farm cannot exceed the vehicle capacity, hence orders from multiple customers can be loaded into the same vehicle on delivery routes, without exceeding the total capacity of the vehicle. Our problem also considers that any customer can make multiple orders, on different days, during a planning horizon. For instance, if the planning horizon is one week, a customer could generate two orders on two different days. Some customers may also require different products to be delivered together in the same order. Each delivery has a cost that is a function of the location of the customer, the vehicle load, and the number of locations visited in the same route.

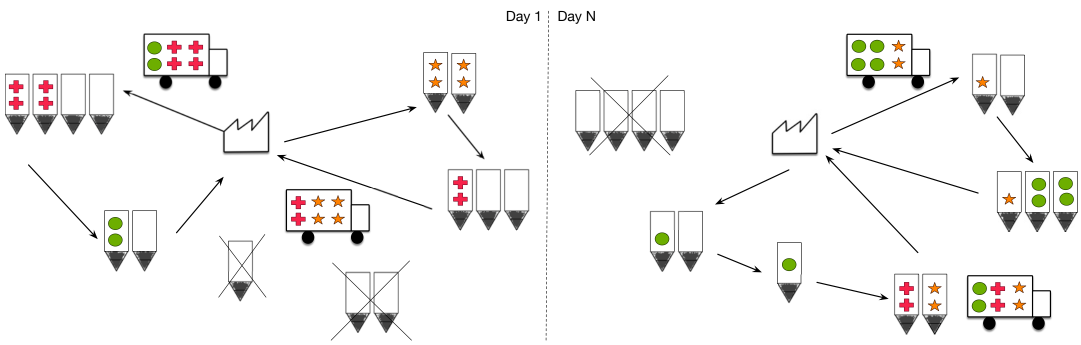



FIGURE 5.3: Representation of our real-life problem. A truck fleet daily transports multiple products and quantities to farms' bins following distinct routes. Product types are represented as geometrical shapes and colors.

The following list summarizes the considered constraints:

- Demands from a set of customers have to be serviced over a time horizon composed of different periods.
- Customers might request different types of products, which are available at some depots.
- Products cannot be mixed inside the same vehicle's compartment (the vehicles have multiple compartments).
- A fleet of heterogeneous and multi-compartment vehicles is available. Depending on the location of the customer, it can only be serviced by a subset of vehicles.

- Based on their location, customers might have a sub-fleet of vehicles preassigned. Likewise, depending on the product type, a customer-product combination might have a depot preassigned.
- Some customers might have a specific period preassigned (top priority locations), while others might follow a time-priority order.
- Bio-security constraints: Visiting order constraints are applied to farms with bio-security concerns. In this case, orders to these farms must be grouped into the same services if they are in the same area. Otherwise, orders to these farms must be the last one in the trip. In any case, these farms will be served the last ones at every trip.
- Accessibility to farm constraints: Every farm has its accessibility score, which defines a vehicle class list that can operate within the facility.
- Special farms: Certain class of farms allows to mix medicated and non-medicated feed into the same truck (within separate compartments). Otherwise, medicated products cannot share the same vehicle service as non-medicated products.
- Farms affinity: A list of farms are likely to be served into the same trip if the opportunity appears.
- Farms prioritized weekday: Certain farms are encouraged to be served on certain weekdays.

Finally, the unload time at the customer's site is not considered, and all compartments are emptied at the end of each working day. Therefore, the main objective of this problem consists of minimizing the total delivery cost, formed by both a variable cost and a fixed cost. At the same time, all customers' demands need to be met, and constraints on the classification of different products in isolated compartments must be respected. With regards to the cost function used, the total delivery cost is modeled by a variable cost and a fixed cost. The variable cost is calculated by using specific tariffs, which depend upon the number of stops performed while delivering the orders and the depot location. Notice that variable costs are computed this way due to the existence of a flat-rate agreement between the feed manufacturer and the feed distributor. The fixed cost is computed as a function of: *(i)* the number of routes; and *(ii)* a unitary fixed cost per route or vehicle. This parameter is usually considered in real-world cases, but barely addressed in both the traditional VRP and the multi-compartment VRP. In our case, when such delivery tariffs are considered, variable costs increase after merging routes, and fixed costs decrease due to the reduction in the number of routes. Despite its non-typical objective function, the problem can be classified as a multi-product, multi-compartment, and multi-order VRP. Hence, it is an *NP-hard* problem and, as such, the use of column-generation approaches (Taș, 2020) or heuristic-based approaches is justified whenever the size of the problem goes beyond a certain level.

## 5.3 Literature Review

The use of digitization technologies (Industry 4.0) is not new to many industry fields, including intelligent components inside the process. The Digital Twin (DT) consists of a virtual representation of a production system that is able to run on different simulation disciplines that is characterized by the synchronization between the virtual and real system, thanks to sensed data and connected smart devices, mathematical models and real time data elaboration. The topical role within Industry 4.0 manufacturing systems is to exploit these features to forecast and optimize the behaviour of the production system at each life cycle phase in real time (Garetti, Rosa, and Terzi, 2012). This remote sense, real-time monitoring, and control of devices and physical production generates large amounts of data, which need to be processed, analyzed and evaluated by simulation or optimization tools to enhance the process planning in real-time (Madni, Madni, and Lucero, 2019). An example of a simulation based planning and optimization concept known in many industries is the digital twin (Boschert and Rosen, 2016; Onggo, Corlu, Juan, Monks, and Torre, 2020). A manufacturing DT offers an opportunity to simulate and optimize the production system, including its logistical aspects and may enable a detailed visualization of the manufacturing process from single components up to the whole assembly (Kritzinger, Karner, Traar, Henjes, and Sihn, 2018). Nowadays, the use of DT models in production and manufacturing sectors is extended, but not limited, to production planning —i.e., order planning based on statistical assumptions (Rosen, Von Wichert, Lo, and Bettenhausen, 2015) —, maintenance —i.e., evaluating machine conditions based on descriptive and machine learning (ML) methods (D'Addona, Ullah, and Matarazzo, 2017), or adding transparency to the machine's health conditions (Lee, Lapira, Bagheri, and Kao, 2013)— or layout planning (Uhlemann, Schock, Lehmann, Freiberger, and Steinhilper, 2017). In most of the applications, simulation participates during the process, improving and helping to make better decisions in real-time (Lugaresi and Matta, 2018). In the agro-sector, it is being used in distinct areas like managing crop conditions (Alves, Souza, Maia, Tran, Kamienski, Soininen, Aquino, and Lima, 2019).

Being the farm's feed-stock one of the key assets to map into the digital twin, the need for measuring this stored inventory in a reliable and accurate way becomes crucial to build this decision tool on top. There are few kinds of solutions in the market that have attempted to provide a solution to remotely monitor feed-stocks in livestock farms bins. They either measure a bin's weight or measure the feed level inside the bin. The first approach (weight) uses "load cells", which are installed in the bin's support structure. The second approach (level) uses level sensors usually based on cable, radar, ultrasonic, or guided wave technology. Similar products to our proposal are available on the market —e.g., the 3DLevelScanner Non-Contact Sensor by BinMaster Christensen, 2019. These sensors use a complex radar system to measure a 3D feed surface. However, these sensors are not fully appropriated for our environment due to: *(i)* their high cost, which makes large deployments unaffordable; and *(ii)* the physical principle they rely on, which does not allow them to provide accurate and reliable data in small bins like the ones our environment present – fibber manufactured bins with a cylinder diameter of up to 3 meters. Measuring stock level within the bin is difficult, since the feed surface is uneven – the difference between the lowest and the highest points can easily reach 2 meters. Since level sensors only measure the distance between the device and a single point in the feed's surface, measures have a lack of accuracy (Carson, 2000). The only solution in the market able to provide accurate measures are the load cells. However, their installation costs are extremely high —€3,000/bin including installation— for the market niche this work targets. Moreover, devices with the lowest price —ultrasonic and guided wave radars— cost around €1,200 per bin, in addition to €150 to €300 for annual maintenance and communication services. Furthermore, the functionality obtained by the suppliers' standard software is limited to a daily record of the levels in the bins. If the customer requires a higher level of integration —which is the most common situation, since a single feed supplier manages several farms—, the customization will further raise the final price. With regard to sensor network deployment and operations scalability, most of the solutions which are already on the market must be mains powered, which raises the installation costs. Additionally, some farms have electricity generators which are only active for certain hours per week, failing to supply all-day power to the devices and making them non-operable most of the time. Deployments with such devices have uncertain profitability, which inhibits a successful market uptake. Of course, several sensors are present in the literature that try to address similar problems in the smart city environment, like the waste collection (Chandra, Sravanthi, Prasanthi, and R, 2019; Folianto, Low, and Yeow, 2015). However, none of them reach the required accuracy to measure bulk solids stored in farm bins.

Lastly, this work faces the well known VRP, one of the most studied problems in the field of combinational optimization. Despite that, the academic community is still highly interested in proposing new and better solution methods, since they incorporate highly realistic constraints, especially when these are considered simultaneously (Azadeh and Farrokhi-Asl, 2019). Characteristics that affect data input, as well as constrains on fleet configuration or on time, turns a classical VRP into a rich VRP (Caceres-Cruz, Arias, Guimarans, Riera, and Juan, 2014; Lahyani, Khemakhem, and Semet, 2015). The physical properties of vehicles are one of the main parameters of own problem. Vehicles can be homogeneous or heterogeneous, fixed or unlimited, and compartmentalized or not. Its relevance arises from real-world cases in which a set of incompatible products must be delivered to a set of heterogeneous customers, i.e., each customer demands a subset of different products, which cannot be mixed. The most used strategy in those cases is using compartmentalized vehicles. The literature on rich VRPs dealing with the multi-compartmental fleet is also split into deterministic and stochastic approaches. The works by Silvestrin and Ritt (2017), or Muyldermans and Pang (2010) consider stochastic demands. Dynamic programming approaches to solve this problem are widely used (Pandelis, Kyriakidis, and Dimitrakos, 2012; Tatarakis and Minis, 2009). The waste collection activities and apparel, fuel, and food industries motivate the research applied to real-world cases (Reed, Yiannakou, and Evering, 2014; Wang, Ji, and Chiu, 2014). Petrol and food industries are presented as typical realistic examples where compartmentalized vehicles are necessary (Coelho and Laporte, 2015). Including inventory decisions in routing is usual in these cases (Popović, Vidović, and Radivojević, 2012). The products perishability (Tordecilla-Madera, Polo, and Cañón, 2018) or supply and demand seasonality (Vlajic, Vorst, and Haijema, 2012) are very common in the agri-food supply chain. Even though works that deal with the cleaning activity are scarce, in Oppen, Løkketangen, and Desrosiers (2010) the cleaning activities are also considered in a multi-compartment VRP with inventory constraints. They solve the so-called livestock collection problem through an exact solution method based on column generation. Animals from different types and categories are transported, and they cannot be mixed in the same compartment. Finally, an interesting problem arises when considering flexible compartments, i.e., the number and capacity are variable in each vehicle. For instance, Hübner and Ostermeier (2019) propose a Large Neighborhood Search (LNS) algorithm to solve this problem while loading and unloading costs are considered.

The described real-life problem shows a set of characteristics that increases its complexity –in comparison with the typical rich VRP– namely: (i) constraints regarding multiple compartments, products, and orders simultaneously; (ii) an objective function considering delivery tariffs; (iii) restricted origins in a multi-depot problem; (iv) the consideration of multiple KPIs; and (v) an imposed sorting on farm visits within the same route, due to customers' requirements or biosecurity concerns, which introduces temporal dependencies among farms. In order to include all these characteristics, a flexible solving approach is needed. Besides, being an NP-hard problem, exact approaches are not able to provide 'agile' solutions as requested by the food distribution firm. Hence, a flexible and fast heuristic is proposed in this work.

## 5.4 Methodology

The implementation of this digital twin looks to answer three questions: *(i)* which precise bin needs to be replenished?; *(ii)* which specific feed diet needs to be served and what amount?; and *(iii)* when do we have to deliver this order? There are two main sources of information available that allow to plan ahead the theoretical diet sequence. First, the feed-stock measured by using remote monitoring sensors and, second, the nutritional plans designed by livestock managers (Brossard, Nieto, Charneca, Araujo, Pugliese, Radović, and Čandek-Potokar, 2019). The physical feeding area (barn plus feed storage) is mapped upon our digital twin.

Figure 5.4 depicts the modeling framework followed in this paper. First, identifying a demand pool consists of knowing the current stock levels (1), in order to estimate the inventory lifespan (remaining days of stock, ETA) according to a consumption trend (2). By following the nutritional plan, quantities and diets are known taking into account the breed size eating from the analyzed feed area (4-5). The demand pool is built up by including bins that reach the user defined thresholds on inventory lifespan (3). Once the demand is identified and specific orders are confirmed, the system schedules the refilling services following the considered constraints, using the available truck fleet (7-8).

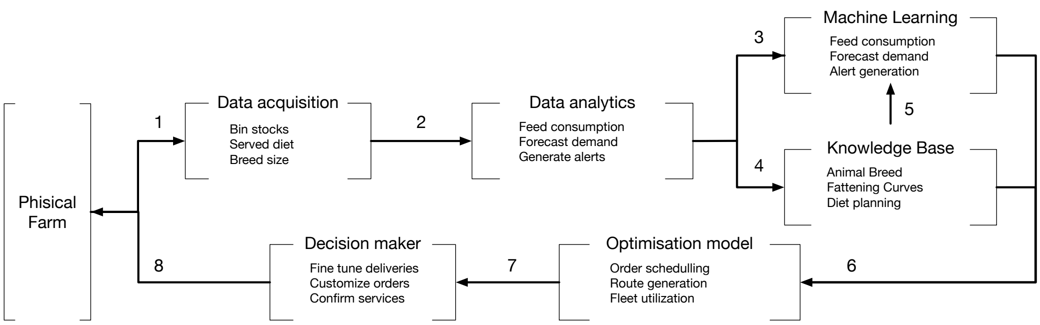



FIGURE 5.4: Proposed framework to model the Digital twin concept in a livestock farm.

### 5.4.1 Data Acquisition & Demand forecast

Once feedstock levels are easily recorded from every bin (See Chapter 2), forecasting the next order consist on quantifying the stock's lifespan and to identifying the next product to be served. The available feed stock will cover a larger or shorter period of time depending on the number of animals that are eating from the feeding system, and its growing stage. Simplifying, the lifespan has been quantified by using the feed intake rate. Two indicators arise from using the feed stock time series made of hourly readings: a) The current consumption rate (CR), b) the Daily consumption rate (DCR) and c) the average daily consumption rate (ADCR). While DCR is estimated using the readings available for the same day, ADCR measures the daily average consumption reached taking into account a certain time window. Users can define the number of days considered. As a rule-of-thumb, two days are typically considered to estimate this intake rate. At every new reading, ADCR is applied to the current stock level to estimate inventory's lifespan in days (ie: an inventory of 4200t with an ADCR of 600kg/$day$ would lead us to $7days$ of feed stock). We are not considering animal growth stages for this projection. These rates will allow us to estimate the stock lifespan in terms of number of days (ETA). It is assumed that near future intakes will follow the ADCR for a given time window.

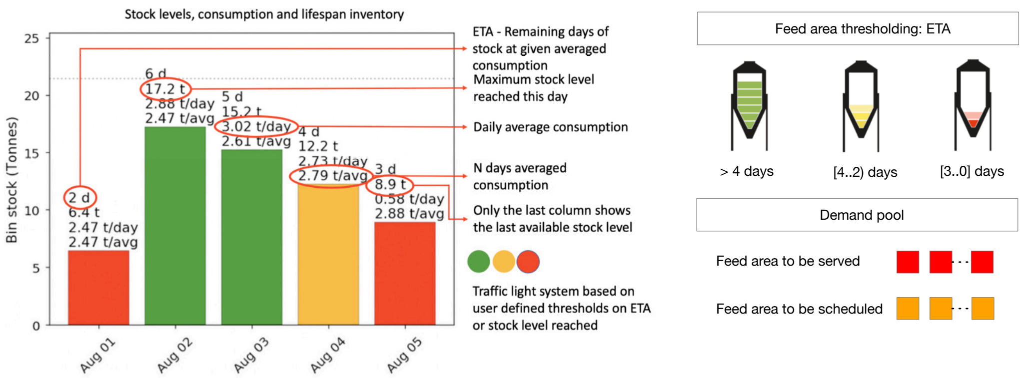



FIGURE 5.5: From inventory lifespan (ETA) to demand alert generation: Traffic light system with color coding based alert generation. The feed area threshold shown in this Figure exemplifies the three states: First inventory lifespan over 4 days (green), between four and two days of stock (yellow/orange), and inventory lifespan below 3 days (red).

Farmers typically allocate the animals into barns with its own feeding facilities (bins, feeders, stables, etc.) Each barn consume the feed from their assigned bins. Animals within the same barn follow the same feeding program (*Feed Area*), so knowing the number of animals and the production plan, new orders can be settle down taking into account the storage capacities, the animal intake rate and other feed freshness constraints. The theoretical animal intake rates are used to estimate each delivery lifespan. This initial product scheduling is used to track the real consumption on farm, by matching the real stock with the expected stock lifespan. It is defined a threshold for every *feed area* (Figure 5.5). This threshold may be based on the remaining percentage of stock or the ETA value. Once this threshold is reached a demand alert is raised. Hence, this specific feed area enters into the *demand pool* according to its ETA value. So far, the system generates an alert stream containing the feed areas that will run-out-of-stock without a promptly refilling. The next phase consumes this alert stream to plan ahead this demands, and compose the precise orders to be served according to the nutritional plan and the supply chain constraints. The system generates the expected order scheduling according to the nutritional plan and the total quantity to be served, sliced into multiple orders to do not exceed the capacity constraint imposed by the farm facility.

### 5.4.2 Scheduling heuristic

The BP1 model seeks to provide accurate real-time information for daily tracking of food consumption in the farm, plan the order ahead, and suppress the stock ruptures (run-outs). The evolution of BP1 consists in shifting the order execution from the farmer to the vendor, which is still BP1. BP2 appears when the vendor starts to plan ahead its services and optimize its fleets by knowing in advance the demand pool. Yet, while BP1 produces the demand pool, feed quantities for the next services are still manually placed by feed vendors according to the feeding plan agreed with the farmers. Then, the BP2 allows feed vendors to optimize their fleet utilization and the service routes. At this point, the method feeds a demand pool with orders, ready to be confirmed. Once those orders are selected to be served (initially by human supervision), a metaheuristic framework elaborates several delivery plans according to a variety of key performance indicators (KPIs). This metaheuristic makes use of biased randomization techniques (Juan, Faulin, Jorba, Riera, Masip, and Barrios, 2011). It also implements a multi-start framework

(Martí, Resende, and Ribeiro, 2013). The heuristic which solves our VRP problem consists of two stages, which are represented in Figure 5.6. While stage 1 aims to build the so called *dummy solution* —setting up the routes assuming individual trips for every order—, stage 2 follows a constructive schema to merge those services —taking into account the given constraints—, so that complete delivery routes are build with the goal of minimizing the overall cost.

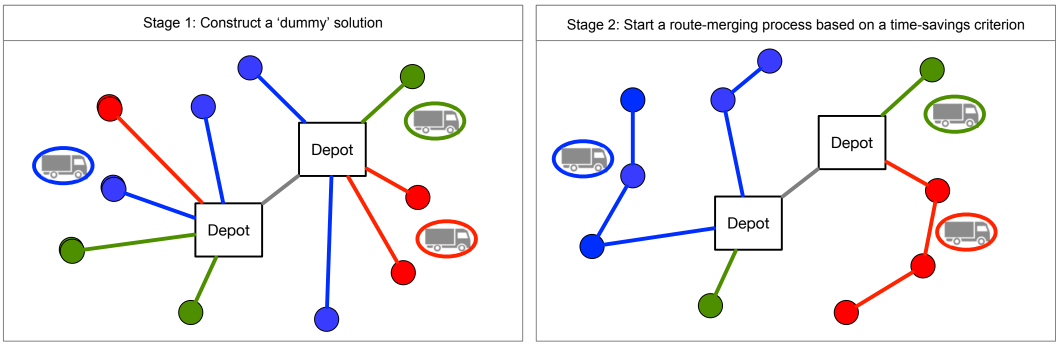



FIGURE 5.6: Proposed solving approach with two-phases heuristic. First a constructive phase with the point to point solution, and second the merge process to achieve a near-optimal solution (Departing from the same depot, colored the same trip with its stops).

Algorithm 8 displays the heuristic pseudo-code, which encompasses the next steps. Initially, customers are sorted according to the given prioritization. Next, a dummy solution is generated where every $(customer, product)$ is visited in a single round trip (stage 1). Then, stage 2 starts by computing the list of pairs of routes or services $routesToMerge$ that can potentially be merged. This merging criterion relies on a distance-based savings value. Each savings value is associated with each pair of routes, i.e., given two customers, a savings value is assigned to the direct service that connects them. The savings value represents the savings in distance generated by serving both customers in the same route, instead of one route for each customer. This list, $routesToMerge$, is sorted by distance-based savings values into descendant order, and traversed. In each iteration the algorithm picks a pair of routes, $pairRotues$, from the list $routesToMrege$ in a randomizing manner, using a geometric probability distribution as proposed in (Juan, Faulin, Jorba, Riera, Masip, and Barrios, 2011). The merging conditions are checked: *(i)* priorities in order of visiting customers; *(ii)* each customer belongs to different routes or services; *(iii)* each customer is connected directly to the depot; and *(iv)* the total vehicle capacity and each compartment capacity layout fits with the resulting demand. If all constraints are met, then the solution is modified replacing these two routes by the merged one, thus reducing the solution total distance. Finally, when no merges are available, the algorithm ends.

```
customers ← sortingByPriorities(customers)
solution ← dummySolution(customers)
routesToMerge ← generateSortedListBySaving(customers)
while routesToMerge ≠ ∅ do
    pairRoutes ← biasedSampling(routesToMerge)
    if isMergePossible(pairRoutes, solution) then
        solution ← merge(solution, pairRoutes)
    end if
    routesToMerge ← remove(routesToMerge, pairRoutes)
end while
return solution
```

**Algorithm 8:** Biased Randomized Heuristic

In order to improve the quality of the solutions provided by our heuristic approach —and also to keep a pool of good solutions according to all KPIs—, we integrated the heuristic into a multi-start framework, which is showed in Algorithm 9. The multi-start approach is a high level method that is characterized by running several times the randomized heuristic, thus performing a better balance between solution robustness, quality, and time requirements (Martí, Resende, and Ribeiro, 2013). Our multi-start method starts by generating an initial solution using the heuristic in a deterministic manner, and then computing the associated KPIs (distance, number of services, cost and vehicle utilization). This initial solution is set as the best-so-far solution in all the KPIs. Unlike the classical VRP problems, our solution cost is computed by employing the specific tariff given by the supplier, i.e.: the flat-rate delivery tariff that considers if each service is single/multiple-trip, as well as the total demand. The algorithm iterates until the maximum time is reached. For each iteration, a new solution *solution* is generated using our heuristic in a biased-randomized mode. This new solution *solution* is compared against the pool of *bestSolution*, not only in terms of cost, but also taking account the rest of KPIs. If the new solution *solution* is better than any of the pool *bestSolution* in any KPI, then *solution* replaces it. Finally, the algorithms ends returning the pool of best solutions *bestSolution*.

$bestSolution \leftarrow BiasedRandomization(customers, False)$
$kpiBestSolution \leftarrow computeKpis(bestSolution)$
**while not** maximum time reached **do**
    $solution \leftarrow BiasedRandomization(customers, True)$
    $kpiBaseSoluton \leftarrow computeKpis(solution)$
    **if** $kpiSolution < kpiBestSolution$ **then**
        $bestSolution \leftarrow replace(solution,\ BestSolution)$
        $kpiBestSolution \leftarrow replace(kpiSolution,\ kpiBestSolution)$
    **end if**
**end while**
**return** $bestSolution$

**Algorithm 9:** Multi-Start VRP-MPCO

## 5.5 Results

Figure 5.7 presents the implemented system and the scope of the project in terms of business process validation. In order to validate the BP1 proposition, an inventory remote monitoring system has been developed and deployed. This has enabled the farmers and feed manufacturers to remotely check the feed stocks, measure the daily intake rate, and raise the refilling alerts per silo according to some user defined thresholds. The BP2 has embraced the same BP1 assumptions, while the next product to be ordered and its quantities are automatically proposed following the given feeding programs. BP2 also provides the supply chain actors with an automatic order distribution planning that configures the truck loads and the delivery routes following certain constraints.

Sensor networks with 225 devices for the Spanish Pilot and 50 devices for the UK pilot have been deployed. Although this work does not include results from the third pilot, another 50 devices have been deployed for a Swedish partner. These deployments have allowed us to validate the device accuracy and durability, including its resilience under distinct weather conditions. The system has been collecting data for a working period of 12 months. We have assessed a good functionality of the sensor, not only in terms of data accuracy and repeatability but also in terms of usability and deployability. It takes 20 minutes to install and configure it in a bin without a ladder, and even less if a truck mounted crane is not needed (ladder availability).

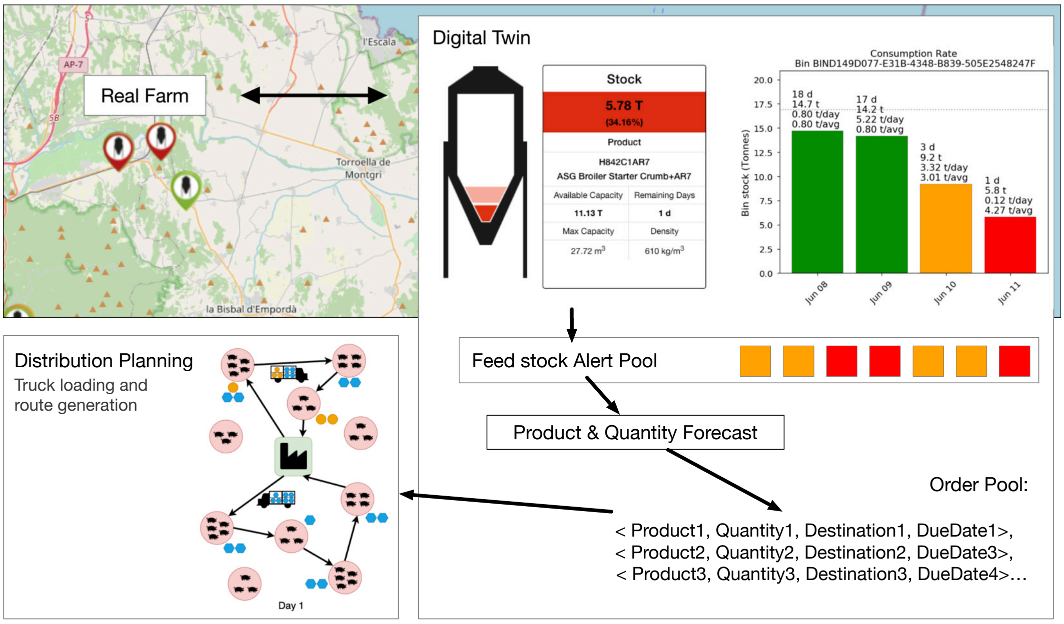



FIGURE 5.7: Overview of the developed digital twin and delivery planning system.

We have established an incident management process that allows us to provide a data service to our partners. We also offer a service level agreement (SLA) to our partners. Any issue with the estimation service (software side) is managed and solved within the next working day after being raised. Issues with the hardware deployed (sensors) are attended and diagnosed in 24h. After the diagnosis, if substitution is needed, an urgency level is assigned to each required substitution. This is regulated by the pre-agreed SLA. In the worst-case scenario, the defective device is substituted in 72h. In terms of sensor failure, with more than 300 sensors deployed to date within these pilots, we just needed to perform 3 substitutions. That represents a failure rate of 1%. In order to handle the installation or replacement operations, we conducted specific training with local technicians at every area where our customers are located. Hence, after an issue has been identified, it is easy for us to arrange the substitution operation with those third parties. The lock-downs and restrictions on movement adopted by the United Kingdom, Spain, and other European and Eastern countries due to the COVID-19 have affected our device manufacturing process, assembly, and deployment. However, by April 2021 the device deployment has reached a total 90% of the initially planned deployment. This has allowed us to achieve the goals of the IOFEED project. Regarding fleet operations and availability, these issues have not been considered in these pilots.

During this period, specific goals have guided the evaluation in both partners. The UK pilot has focused on testing how the availability of accurate inventories and demand forecast benefit their logistics (BP1). In addition, the Spanish pilot has also validated how order scheduling can be added to system in order to enable a complete VMI system (BP2).

### 5.5.1 Implementation at Dugdale Nutrition

In parallel with the IOFEED project, people from the Dugdale's logistics department were executing an internal pilot called "Premonitions Project (PreP)". Its goal was providing their sales representatives (Reps) with updated customer requirements through an active process of chasing customers by doing direct calls, asking for the current stock in their

| **Time spent on Baseline clients** | **6-7 hrs per day** |
|---|---|
| Target 1. Based on manual client monitoring seeks to providing reps with updated data on expected customer requirements and seeks to reduce the time for sales reps. | 1.1 Ring every single customer for a rep to check feed levels<br>1.2 Check ERP software for previous orders and pulling data<br>1.3 Spend at least 10 minutes for each rep to send data for premonitions |
| **Time spent on BP1 clients** | **55 mins avg. per day** |
| Target 2. Seeks to providing accurate real-time information for daily tracking of food consumption in the farm, plan the order ahead, and suppress the stock ruptures (run-outs). | 2.1 Open IOFEED, checking map (who is red and yellow), write everything down, check alerts, identify orders. – 15 mins avg.<br>2.2 Go into ERP to look at products to see when they last had it and what product – 30 mins avg. (if sales data was in IOFEED reduced to 5 mins)<br>2.3 Ring Rep to get confirmation on processing orders - 10 minutes avg. |
| **Time estimate on BP1 + VMI** | **20 mins** |
| Target 3. Aims to change the business strategy moving the workload balance of maintaining the food stock to the feed supplier. Vendor Managed Inventories without route optimization or automatic fleet configuration. | 3.1 Would have to ask rep on if he would be okay with removing phone call, this would come with trust of IOFEED orders. Payment reasons would be main reason not lack of trust in IOFEED.<br>3.2 Gives confidence for the feed manufacturer to act and chase reps and argue her point and push with transport. Target to reduce time spent per customer (rep) reduce from 1hr 30mins to 20mins |

TABLE 5.1: IOFEED impact on order forecasting and order confirmation

silos and gathering information about their production plan. This premonitions project gives them a deep understanding of their customers with more positive interaction with them. Reps gained time to talk to customers, focusing on up-selling and cross-selling with them, and opened up potential sales with prospects identified by current clients. The IOFEED project ran side-by-side with their internal pilot. This special scenario allows us to identify what internal processes were done and measure how IOFEED improved their business' processes. At the beginning, sales representatives were reluctant to accept changes. However, they finally understood the project and were interacting and engaging in a very positive way. Dugdale's logistic managers were involved in the PreP, targeting a 10% increase in new customers and sales, which in turn would be a 10% increase to revenue over the first year. Table 5.1 shows how IOFEED positively affected the PreP, and provides knowledge and a way of working that was not possible before – as recognized by the Dugdale's logistic managers. With the implementation of the IOFEED system, workload produced by PreP activities can be assumed by the current staff.

Additionally, IOFEED gave confidence in conversations with customers, Dugdale's advise gains credibility. IOFEED could be incredibly useful for the confidence it creates both with staff and customers, and to grow relationships with their customers. IOFEED service shows direct impact on livestock feeding logistics. First, clearing the activity of stock run-outs. An average run-out cost was estimated to be £97, based on the first four months of 2019 cost of run outs, averaged out. Cost for each run-out is based on admin cost (wage per hour) driver wage, fuel cost and loss of truck space. On average, one hour of admin work was needed for each run-out. These costs were quantified on £14k for a six month period. Orders are now being put in advance (2-3 days) with To-Be-Confirmed (TBC) status using IOFEED. This saves a gap on the truck. It has shown a positive effect on planning and it has provided a base to build other orders around saving a lot of time. Everything indicates that having a larger sensor deployment would positively affect feed production, smoothing the production curve by forewarning the products and quantities to produce in a wider area.

The agri-food sector has been named as one of the most affected by the UK's exit (Brexit) from the EU. From the IOFEED service provisioning perspective, the sensor will need to file customs declarations. In terms of service provisioning, IOFEED service is starting to set up a branch office in UK territory. This will enable the service provisioning completely unaffected by Brexit considerations.

### 5.5.2 Implementation at Batallé Group

In terms of BP1, the implementation at the Spanish partner contributed in a similar vein. In contrast to the UK pilot, Batallé Group operates with production contracts between them (the livestock owners and feed suppliers) and the farmers (the facility owners) to have the farmers raise the livestock on their farms. Hence, as the farmers are partly paid by a facility rental, any actuation on controlling each livestock growing period would lead them maximize the profits. Irregular livestock feeding affects the growing rate (Johannesson and Ladewig, 2000). Therefore, suppressing the run-outs may affect positively the animal growth, avoiding ordering feed in excess reduces the feeding costs by avoiding inventory relocation tasks. Finally, as the UK pilot confirmed, workforce dedicated to chase farmers is dramatically reduced. Additionally, they pointed out their interest in exploring the opportunity to differentiate normal intake patterns from abnormal consumption patterns that may appear. This intake rate fluctuation may correlate with non-optimal feed quality or anticipate an animal disease. Although direct benefits to the farmers might seem negligible, the opportunity cost of not having accurate inventory reports is huge. A wrongly reported inventory may produce an over-sized or not required order, which in turn means unnecessary costs. In order to comply with bio-security regulations, farm facilities must be kept empty and cleaned for a period of time. This means that every time a bin has more than one ton of feed not consumed before animal relocation to the slaughterhouse, this feed needs to be removed with specific equipment. The Spanish pilot has recorded an average of 20 operations per month with a cost of €175 per actuation, which means an average cost of €30k per year. These costs are likely to be saved by controlling the stocks accurately as the run-out costs measured at the UK pilot.

Regarding the evaluation of the BP2, the Spanish pilot has provided the real schedule of its designed routes for a period of 44 weekdays. Given the experience of the staff, Batallé has traditionally designed the routes by hand, spending several hours per week in this labor. Conversely, our algorithm is designed to generate a set of good solutions in only a few seconds. Our designed heuristic considers 4 KPIs to assess each solution quality: total traveled distance, total cost, total number of routes, and average vehicle utilization. The latter refers to the load quantity that a vehicle transports in each route, as a percentage of its total capacity. Then this KPI is calculated as the average of all routes in the solution. Finally, our algorithm yields 4 solutions per run, where each solution is the best one according to each KPI.

Table 5.2 shows the average results obtained by our greedy heuristic, i.e., a single non-random run is performed in this case. Each number is calculated as an average of the values yielded by our $44$ instances. Firstly, the real-life results obtained by Batallé are displayed. Then we show the $4$ solutions yielded by our heuristic, assessed in terms of each KPI. The underlined number indicates our best-found result for each KPI. The KPIs distance, cost, and number of routes are better when they are smaller, and the utilization is better when it is greater. Additionally, the columns of gaps show the average percentage difference between our solution and Batallé's. All gaps are better when they are lower. A negative gap indicates that we outperformed Batallé's results, i.e., our agile greedy heuristic is able to find both smaller distance and costs than the company. Regardless of the type of solution, the cost gap is always negative and less than $1\%$. This difference is not greater given the use of the flat-rate tariffs. Hence, the cost improves when the other KPIs get worse, and vice versa – which indicates that the solution to be selected by Batallé for their daily routes depends on the KPI to optimize. Finally, the average number of routes is the same for both *Best-#routes* and *Best-utilization* solutions. However, the distance and utilization KPIs are worse in the *Best-#routes* solution, and the improvement in cost is very slight. Therefore, we can assume that the *Best-utilization* solution always outperforms the *Best-#routes* solution.

| Type of solution | KPI | | | | Gap ORTBS vs. ABS | | | |
|---|---|---|---|---|---|---|---|---|
| | Distance (km) | Cost (EUR) | #Routes | Utilization | Distance | Cost | #Routes | Utilization |
| Batallé | 1153.6 | 5555.5 | 23.9 | 95.8% | | | | |
| Best-distance | 1124.7 | 5544.0 | 25.0 | 91.4% | -2.6% | -0.2% | 4.9% | 4.4% |
| Best-cost | 1153.3 | 5512.4 | 25.4 | 90.3% | -0.1% | -0.8% | 6.6% | 5.5% |
| Best-#routes | 1207.9 | 5531.4 | 24.8 | 92.4% | 4.6% | -0.4% | 3.9% | 3.4% |
| Best-utilization | 1186.2 | 5534.5 | 24.8 | 92.6% | 2.5% | -0.4% | 3.9% | 3.1% |

TABLE 5.2: Average Batallé solution (ABS) and Our average real-time best-found solutions (ORTBS).

Table 5.3 shows the average best-found results obtained by our biased-randomized heuristic after 1-minute run time. Obviously, results shown in the row corresponding to the Batallé solution are the same as in Table 5.2, since they do not depend on our algorithm runs. In general, our results in Table 5.3 outperform those in Table 5.2, which is more evident if we observe the underlined gaps. Regarding the cost, using flat-rate tariffs means that achieving large improvements is difficult. A previous test allowing only dummy solutions was performed to assess this hypothesis. In this case, an average cost of $5,466.1$ was yielded, in a scenario where routes are designed considering only one-farm round-trips. Such value is a lower bound for the cost, i.e., this is the best possible cost that can be obtained, with a minimum average cost gap of $-1.6\%$. Nevertheless, this result is not admissible for the company, since the rest of the KPIs falls to unacceptable levels. Conversely, our biased-randomized heuristic yields well-balanced results. For instance, the column corresponding to the cost gap in Table 5.3 shows that we preserve the negative gaps already obtained in the Table 5.2 results, with a deterioration that is really small when compared to the improvement in the underlined distance, number of routes, and utilization KPIs. Finally, as well as in the case in Table 5.2, we can assume that the *Best-utilization* solution outperforms the *Best-#routes* solution.

## 5.6 Conclusions

A remote monitoring system is built around a 3D camera based sensor to quantify feed inventories stored in bins. The IOFEED project makes use of this system to monitor inventories in farms, enabling a data service that allows feed manufacturers and farmers to remotely control their feed stock levels. Two pilots have been set up with $50$ sensors each

| Type of solution | KPI | | | | Gap OBRBS vs. ABS | | | |
|---|---|---|---|---|---|---|---|---|
| | Distance | Cost | #Routes | Utilization | Distance | Cost | #Routes | Utilization |
| Batallé | 1153.6 | 5555.5 | 23.9 | 95.8% | | | | |
| Best-distance | 1104.0 | 5541.7 | 24.7 | 92.5% | -4.4% | -0.2% | 3.5% | 3.3% |
| Best-cost | 1201.3 | 5495.7 | 26.7 | 86.2% | 4.3% | -1.1% | 12.3% | 9.6% |
| Best-#routes | 1178.8 | 5544.3 | 24.2 | 94.1% | 2.0% | -0.2% | 1.4% | 1.7% |
| Best-utilization | 1168.5 | 5549.6 | 24.2 | 94.8% | 1.1% | -0.1% | 1.4% | 1.0% |

TABLE 5.3: Average Batallé solution (ABS) and Our average biased-randomized best-found solutions (OBRBS).

(100 sensors in total). After six months of system validation, the IoT system is integrated into the every-day workload of the farmers, and has allowed to determine what are the system's benefits. Relevant benefits have been quantified in optimizing the feed supply chain to farm by reducing workforce dedicated to chasing client's orders (96% reduction on order management), suppressing run-out and feed relocation costs (up to €62/bin/year). Additionally, for the evaluation of the BP2, the Spanish pilot has provided their order scheduling for a given period of time. Costs are evaluated by using their service scheduling and were taken as reference costs. Results obtained by the proposed heuristic to solve the vehicle routing problem show an improvement over the use of a flat rate tariff. Furthermore, the proposed decision support system allows the distinct stakeholders to analyze alternative scenarios taking into account several target key performance indicators, such as distance, cost, number of routes, and truck utilisation. It is interesting to point out that during these pilots we have experienced some implementation barriers with farmers. They typically focus mainly on their core business, and have little or no interest in data gathering. Main concerns have been experienced in technological trustworthy, where the "lack of rust" was perceived as a negative factor. Reliable technology is required to encourage farmers into low-risk implementations, even in the scenarios where they are not the facility owners. Although it is commonly accepted that smart farming requires information sharing across supply chains, farmers are still often not willing to provide access to their data in light of uncertainties about ownership and security concerns. While these concerns tend to dilute when they are not the real owners of the facility, the implementation of policies to give farmers ownership of their data will be required. All the actors of the value chain seek proven results of direct impact and improvement potential on individual farm and supply chain levels.

# Chapter 6

# Conclusions and Future Research Lines

Making a product is just an activity, making a profit on a product is the achievement.

Amit Kalantri, Wealth of Words

The feed industry has a low digitalization level. Control of the feed stocks is done by farmers in an inefficient way (e.g. they hit them with a mace to acoustically guess stock level). When silos are empty, farmers send a refilling order to the feed supplier, who must manufacture and deliver it in just 24-48 hours. This method force feed suppliers to work on-demand and impede to optimally organize their logistics. Furthermore, the lack of an accurate method for measuring the stocks in the farms is the cause of important over costs due to urgent orders caused by run outs and orders with wrong quantities. All this problems could be solved if feed suppliers had access to the farms' stock levels, the appropriate tools for optimizing their logistics and the consent of the farmers to decide the appropriate moment and quantity to refill each silo. The Vendor Managed Inventories paradigm has been implemented with great success in other industries. Unfortunately, the feed industry has never had advanced software solutions to digitalize its supply chain.

## 6.1 Main research contributions

This thesis proposes a "digital twin" for the feed supply chain on the livestock farm that enables interactions between a physical system and its computational model representation. It creates a virtual world that corresponds to the real-world system that is being controlled by a simulation model. In this thesis, the symbiotic simulation creates the representative virtual world of a livestock supply chain which includes inventories at the farmers, the warehouse(s) and the logistics of the food supply. This allows us to evaluate different business policies. Since we can represent the system as a network of queues (e.g. items in the warehouse waiting to be transported, items in transport waiting to be unloaded).

The EU-IoFEED project (https://www.iof2020.eu), which aims at monitoring approximately 325 bins and investigate business processes carried out between farmers and animal-food producers, has framed the works presented in this thesis. Initially, two test-beds have been set in two distinct European countries, the United Kingdom (UK) and Spain (ES). The UK has a partner with 50 bins, while the Spain has a single partner with 50 devices. After this initial phase, the number of monitored bins has increased up to 175 more for the Spanish pilot. Two business processes will be put to test in this project, which will analyze their cost-benefit and cost-effectiveness: *(i)* business process 1 (BP1), focused on farmers; and *(ii)* business process 2 (BP2), focused on helping to animal-food manufacturers. BP1 aims at providing the best solution for farmers to achieve a seamless procedure to measure bins' stock. The goals are: to provide accurate real-time information for daily tracking of food consumption in the farm, to assess feeding costs, and to help the farmer to increase his/her feed conversion rate, including a reduction in stock ruptures. Additionally to BP1 benefits, BP2 aims to change the business strategy moving the workload balance of maintaining the food stock to the feed supplier, so they can handle and manage the correct and exact amount of food for each bin that covers their client needs (the farmer) while, at the same time, optimizing the supply chain cost (production, own stocks, product shipping/distribution, etc.).

Contributions of this thesis can be summarised in three main fronts:

1. **A remote inventory monitoring system**: The sensor developed during this thesis can be installed in 5 minutes and it has a maximum error below 5%. Thanks to a 3D volumetric sensor, opens the possibility of a massive deployment of sensors on the livestock farms. As an eco-friendly IoT integrated solution, this sensor counts with a solar-based battery, which makes it independent on farm's electrical grid. This is a completely disruptive approach: Now, isolated farms can have their silos remotely monitored, automatically able to generate data and send it to a cloud-based platform, where they are accessible anytime, anywhere and through any device. Feed suppliers can optimise their inventories, production batches, delivery routes and raw material purchases. Farmers have the opportunity to have a clear 3D picture of their farm daily feed intake, enabling them to optimise resources and better calculate their livestock feed conversion rate. They also avoid possible contamination, since temperature and humidity inside the silo are monitored to achieve optimal storage conditions.
2. **Combining strategy of an IoT system with simulation-optimization**: This is a reactive approach for the multi-period and stochastic inventory routing problem. The proposed approach, which is based on the combination of a biased-randomized algorithm with Monte Carlo simulation, allows using sensors to obtain updated data on customers' demands at the end of each period. Based on this updated information, the supplier can re-optimize the distribution process for the remaining periods. This methodology aims to determine and quantify if the use of real stock data might improve the optimization results obtained by other existing approaches in the literature, which do not consider this reactive behaviour.
3. **A symbiotic simulation system applied to a real-life scenario**: When automating and optimizing the logistics of animal feed distribution over a given set of real farms, orders can be of multiple types of feed products. These orders are shipped from multiple depots by using a fleet of heterogeneous vehicles with multiple compartments. The capacity of each compartment is known and fixed, although each order can easily be split into independent compartments in the same vehicle. Even though, it is forbidden to mix distinct products into a single compartment since they are incompatible. The total quantity ordered by each product and farm cannot exceed the vehicle capacity. Hence, orders from multiple customers can be loaded into the same vehicle on delivery routes, without exceeding the total capacity of the vehicle. Our problem also considers that any customer can make multiple orders, on different days, during a planning horizon. For instance, if the planning horizon is one week, a customer could generate two orders within two different days. Some customers may also require different products to be delivered together in the same

order. Each delivery has a cost that is a function of the location of the customer, the vehicle load, and the number of locations visited in the same route.

## 6.2 Real-world outcomes

The implementation of the IOFEED system has reduced drastically the workload produced by sales department on chasing orders from clients. Additionally, IOFEED gave confidence in conversations with customers, Dugdale's advice gains credibility at UK pilot. IOFEED could be incredibly useful for the confidence it creates both with staff and customers, and to grow relationships with their customers. IOFEED service shows direct impact on livestock feeding logistics. First, clearing the activity of stock run-outs. An average run-out cost was estimated to be £97, based on the first four months of 2019 cost of run outs, averaged out. Cost for each run-out is based on admin cost (wage per hour) driver wage, fuel cost and loss of truck space. On average, one hour of admin work was needed for each run-out. These costs were quantified on £14k for a six-month period. Orders are now being put in advance (2-3 days) with To-Be-Confirmed (TBC) status using IOFEED. This saves a gap on the truck. It has shown a positive effect on planning and it has provided a base to build other orders around saving a lot of time. Everything indicates that having a larger sensor deployment would positively affect feed production, smoothing the production curve by forewarning the products and quantities to produce in a wider area.

The implementation at the Spanish partner contributed in a similar vein. In contrast to the UK pilot, Batallé Group operates with production contracts between them (the livestock owners and feed suppliers) and the farmers (the facility owners) to have the farmers raise the livestock on their farms. Hence, as the farmers are partly paid by a facility rental, any actuation on controlling each livestock growing period would lead them maximize the profits. Irregular livestock feeding affects the growing rate. Therefore, suppressing the run-outs may affect positively the animal growth, avoiding ordering feed in excess reduces the feeding costs by avoiding inventory relocation tasks. Finally, as the UK pilot confirmed, workforce dedicated to chase farmers is dramatically reduced. Additionally, they pointed out their interest in exploring the opportunity to differentiate normal intake patterns from abnormal consumption patterns that may appear. This intake rate fluctuation may correlate with non-optimal feed quality or anticipate an animal disease. Although direct benefits to the farmers might seem negligible, the opportunity cost of not having accurate inventory reports is huge. A wrongly reported inventory may produce an over-sized or not required order, which in turn means unnecessary costs. In order to comply with bio-security regulations, farm facilities must be kept empty and cleaned for a period of time. This means that every time a bin has more than one ton of feed not consumed before animal relocation to the slaughterhouse, this feed needs to be removed with specific equipment. The Spanish pilot has recorded an average of 20 operations per month with a cost of EUR 175 per actuation, which means an average cost of EUR 42k per year. These costs are likely to be saved by controlling the stocks accurately as the run-out costs measured at the UK pilot.

Batallé's logistics are already highly optimized. With regards to BP2, having obtained a 2% improvement on their distance covered, shown us how the proposed system may behave at a very high level of performance one will be up and running. Taking into account this percentage reduction in terms of distance covered (Figure 6.1), this represents an opportunity cost for Batallé, that is losing by not optimizing the service scheduling. According to the figures Batallé logistics have an opportunity cost saving of EUR 15k

| *Spanish Business Case* | Total distance covered (km) | Total Tones delivered (Tn) | Average load per trip (tn) | Average distance per trip (km) | Yearly trips according avg. weight/trip (kg) | Transported weight by reduced distance | Average tariff per load (EUR) | Opportunity cost (EUR) |
|---|---|---|---|---|---|---|---|---|
| Truck 19Tn | 181,977 | 60.42 | | | | | | |
| Truck 35Tn | 207,504 | 79.84 | | | | | | |
| Total | 389,481 | 140.26 | 28 | 75 | 5,193.08 | | | |
| Optimization factor | 2% | | | | | | | |
| Distance reduced | 7,789.62 | | | | 103.86 | 2,908.12 | 5.40 € | 15,703.87 € |

TABLE 6.1: Opportunity cost by reducing distance covered at delivering the same service with lesser distance (2% reduction scenario).

approximately. This would be the cost that represent to them 103 additional services they would be able to cover with the reduced distances if they would make use of it.

We can evaluate distinct scenarios where this distance reductions could be larger than the obtained by Batallé logistics. Hence, assuming a realistic scenario where the system could deliver a 10% reduction in distances, we would have an opportunity cost of EUR 78k for the same volume of logistics (5,193 trips to farm / year, with average loads of 28Tn).

## 6.3 Potential future research lines

A symbiotic simulation system (S3), sometimes also called a "Digital Twin", is a simulation that is capable of responding to new data while the simulation is running (it is also known as real-time simulation or digital twin). Future research lines will follow the same vein, looking for developing a complete proof-of-concept decision support system (DSS) for real-time decision making with the historical data provided by sensors (e.g. inventory level), from farmers (e.g. purchasing, number of cattle) and logistics company (e.g. lead time delivery). These historical data will be stored in an Enterprise Data Storage System (EDSS) specifically designed and developed. These historical data together with the most recent real-time data from the sensors will provide inputs to the DSS. The decision maker will use the DSS to make daily operational decisions such as consolidation of demands, routing and food procurement plan (supply).

Additionally, it will make sense to explore distinct price flexibility schemes in further works. The system may be able to provide discounts to customers who inform in advance about the amount of feed and the desired delivery date, thus providing discounts in exchange of flexibility for the delivery day for instance. Also, it is still pendant to measure the impact of the system on feed production. An hypothesis-driven validation will be set in place to assess that the IOFEED proposal reduces costs in production by increasing demand planning and forecasting. It is expected that, having the availability to plan the demand, the production curves may be adjusted accordingly. Therefore production costs can be optimized to decrease the feed-mill's costs, while production capacity may be increased.

The main components of the DSS proof-of-concept is shown in Figure 6.1, inline with the work presented in Onggo, Corlu, Juan, Monks, and Torre, 2020. The data acquisition component will be in place for the whole network of storage points (silos). The components that will be evolved in future works are the data analytics & machine learning component, symbiotic simulation component and the optimization component. The objective of the data analytics & machine learning component is to forecast the most appropriate near future parameters for the symbiotic simulation and optimization components. We will use an ensemble of forecasting algorithms and apply several metrics to measure their accuracies. An algorithm that consistently perform better will be given higher weight. One of the main challenges is how we can update the weight of each algorithm over time.

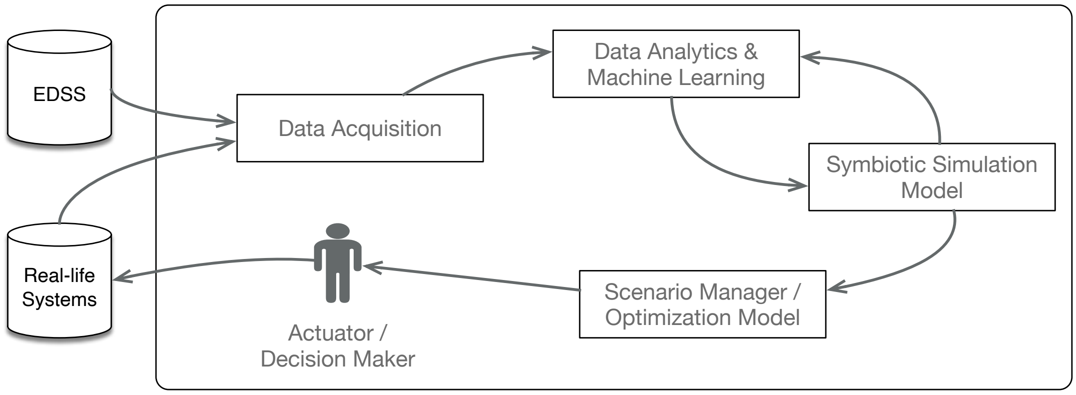



FIGURE 6.1: Symbiotic system formed by an enterprise data storage system, a physical system, and its S3.

We need to find the right sensitivity level towards the most recent real-time data because high sensitivity level will result in unstable system and low sensitivity level will not allow us to make the best use of the most recent real-time data. The machine learning will allow the forecasting algorithms to be adaptive by finding the right balance over time. A discrete-event simulation modelling method may be used to combine the symbiotic simulation with the optimization model so that the optimization model can find the optimal business policy given the uncertainty during the planning horizon (i.e. the time from now to the next decision to be made).

### 6.3.1 Publications

- Raba, D.; Estrada, A.; Panadero, J.; Juan, A. (2020): "A Reactive Simheuristic using Online Data for a Real-Life Inventory Routing Problem with Stochastic Demands". Int. Transactions in Operational Research, 27(6), 2785-2816 (indexed in ISI SCI, 2019 IF = 2.987, Q2; 2019 SJR = 1.018, Q1). ISSN: 0969-6016. https://doi.org/10.1111/itor.12776
- Raba, D.; Juan, A.; Panadero, J.; Bayliss, C.; Estrada, A. (2019): "Combining Internet of Things with Simulation-Optimization in a Food Supply Chain". 2019 Winter Simulation Conference. Maryland, USA. December 8-11, p. 1894-1905, IEEE. https://doi.org/10.1109/WSC40007.2019.9004952
- Raba, D.Tordecilla, R.; Copado, P.;Juan, A.; Mount, D. :"A Digital Twin for Decision Making on Livestock Feeding". INFORMS J. on Applied Analytics, Submited: 5th February 2021. Favourable review. Second review due 23-Jun-2021.
- Vila, O.; Boada, I.; Raba, D.; Farres, E. A Method to Compensate the Errors Caused by Temperature is Structured-light 3D Cameras. MDPI Sensors, 21, 2073. Accepted: 12th March 2021. https://doi.org/10.3390/s21062073

### 6.3.2 Patents

- Gelada, J.; Farres, E.; Raba, D.; Haupt, M.; Gurt, S.: "A Method and a System for Assessing the Amount of Content Stored Within a Container". U.S. Patent No. 10,488,245. Washington, DC: U.S. Patent and Trademark Office, 2019.

### 6.3.3 Conferences & Workshops

- Raba, D: "INSYLO - Animal Feed Supply Chain Optimization". CYTED Workshop. Madrid, Spain. November 28-29, 2016 (oral).

- Raba, D: "INSYLO - Benefits from FIWARE Architecture for an IoT start-up". 1st FIWARE Summit, Malaga, Spain. December 13-15, 2016 (oral).
- Raba, D: "FIWARE Agrifood business case: INSYLO", IoT World Congress, Barcelona. Oct. 25th-27th, 2016 (oral).
- Raba, D: "INSYLO - FIWARE Architecture for an IoT start-up". 1st FIWARE Summit, Malaga, Spain. December 13-15, 2016 (oral)
- Raba, D; "Insylo: The IoT platform for the animal feed supply chain", Cube Tech Fair, Berlin 10th-12th May 2017 (poster)
- Raba, D: "Insylo: Smart Management of silos". 1st FIWARE Summit, Malaga, Spain. November 28th-29th, 2017 (oral)
- Raba,D.; Gruler, A.; Riera D.; Gelada, J.; Juan, A. (2017): "Combining real-time information with a variable neighborhood search metaheuristic for the inventory routing problem: a case study at UBIKWA systems". Presentation. 12th Metaheuristics International Conference (MIC). July 4-7, 2017.
- Juan Perez, J. Panadero, C. Bayliss, L. Martins, A. Freixes, D. Raba. Agile Optimization in Transportation and Logistics . XXXVIII Spanish Conference on Statistics and Operational Research. SEIO - Alcoi. September 3-6, 2019.
- Juan, A.; Faulin, J.; Raba, D.; Freixes, A.; Reyes, L. (2018): "Simheuristic Algorithms for Transportation and Logistics Problems under Uncertainty". Actas del XIII Congreso de Ingeniería del Transporte. Gijon, Spain. June 6-8, 2018.
- Juan, A.; Faulin, J.; Reyes, L.; Raba, D.; Freixes, A. (2018): "Simheuristics: Extending Metaheuristics to solve Optimization Problems under Uncertainty Scenarios". Abstracts del XXXVII Congreso Nacional de Estadística e Investigación Operativa. Oviedo, Spain. May 29 - June 1, 2019
- Raba,D., Gurt, S., Vila, O. and Farres, E., An Internet of Things (IoT) Solution to Optimise the Livestock Feed Supply Chain. International Conference on Cloud Computing and IOT (CCCIOT 2020). April 25 26, 2020, Copenhagen, Denmark.
- Raba, D.; Tordecilla, R. ; Mount, D. ; Riera, D. : "A Digital Twin for Decision Making on Livestock Feeding". Seminar on BigData and Decision Support Systems in Agriculture, 14-16 October 2020. Lleida, Spain. (oral - Best presentation award)
- Raba, D.; Tordecilla, R. ;Copado, P.; Mount, D. ; A. Juan, A. : "A Digital Twin for Decision Making on Livestock Feeding". 2020 Online Workshop SI-Transportation, 10-11 November 2020, Barcelona, Spain (oral)
- Masip, D.; Raba, D.: "Research carrier at UOC - Industrial Doctorate Experiences". 2020 1$^{st}$ Virtual Job Fair at Open University of Catalonia, 16-17 November 2020, Barcelona, Spain (Interview) URL: media, 00:25 onwards
- Raba, D.; Mount, D. : "IOFEED - Use Case 5.5 - Efficiency along the value chain". Future Farming Final Event, 16-18 May 2021. Wageningen, The Netherlands (Online presentation).
- Raba, D.; Mount, D. : "IOFEED - Use Case 5.5 - Feed supply management". Future Farming Final Event, 16-18 May 2021. Wageningen, The Netherlands (Online presentation).

### 6.3.4 Awards, grants and research projects

Along with the academic publications, during this PhD work, INSYLO has secured several grants and awards due to the innovativeness and high technological level of their solutions. Key achievements related to this PhD work are:

- **IOFEED Project (2019-2020)**: A subprogram within the project Internet of Food & Farm 2020 (IoF2020) that explores the potential of IoT-technologies for the European food and farming industry. This collaborative project is funded by the

European Comission by the agreement No. 731884 with EUR 493.6K (use case 2282300206-UC005).

- **Industrial Doctorate MINECO (2016-2020)**: Predoctoral research grant from the Spanish Ministry of Economy and Competitiveness (DI-15-08176), basically covered company expenditures.
- **AGAUR Industrial Doctorate AGAUR (2016-2020)**: Predoctoral research grant from the the Catalan Agency for Management of University and Research Grants (2016-DI-038), mainly covered University expenses and courses.
- **Llavor 2018**: Seed funding to supporting academic initiatives to develop product or business ideas. Awarded through a Catalan grant, co-financed by the European Union through the European Regional Development Fund ERDF (AGAUR-FEDER, reference 2018 LLAV 00017).

# Appendix A

# Cover Pages of Publications

INTERNATIONAL TRANSACTIONS IN OPERATIONAL RESEARCH

I F O R S

WILEY

Intl. Trans. in Op. Res. 00 (2020) 1–32
DOI: 10.1111/itor.12776

INTERNATIONAL TRANSACTIONS IN OPERATIONAL RESEARCH

## A reactive simheuristic using online data for a real-life inventory routing problem with stochastic demands

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**Abstract**

In the context of a supply chain for the animal-feed industry, this paper focuses on optimizing replenishment strategies for silos in multiple farms. Assuming that a supply chain is essentially a value chain, our work aims at narrowing this chasm and putting analytics into practice by identifying and quantifying improvements on specific stages of an animal-feed supply chain. Motivated by a real-life case, the paper analyses a rich multi-period inventory routing problem with homogeneous fleet, stochastic demands, and maximum route length. After describing the problem and reviewing the related literature, we introduce a reactive heuristic, which is then extended into a biased-randomized simheuristic. Our reactive approach is validated and tested using a series of adapted instances to explore the gap between the solutions it provides and the ones generated by existing nonreactive approaches.

FIGURE A.1: Cover Page of Raba et al. (2020).

*Proceedings of the 2019 Winter Simulation Conference*
*N. Mustafee, K.-H.G. Bae, S. Lazarova-Molnar, M. Rabe, C. Szabo, P. Haas, and Y.-J. Son, eds.*

**COMBINING THE INTERNET OF THINGS WITH SIMULATION-BASED OPTIMIZATION TO ENHANCE LOGISTICS IN AN AGRI-FOOD SUPPLY CHAIN**

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**ABSTRACT**

This paper discusses how the Internet of Things and simulation-based optimization methods can be effectively combined to enhance refilling strategies in an animal feed supply chain. Motivated by a real-life case study, the paper analyses a multi-period inventory routing problem with stochastic demands. After describing the problem and reviewing the related literature, a simulation-based optimization approach is introduced and tested via a series of computational experiments. Our approach combines biased-randomization techniques with a simheuristic framework to make use of data provided by smart sensor devices located at the top of each farm silo. From the analysis of results, some managerial insights are also derived and a new business model is proposed.

**1 INTRODUCTION**

In feed manufacturing, distribution, and replenishment planning, efficient decision making can reduce feed stocks, minimize wrong or excessive orders, cut down urgent orders, and limit the impact of uncertainty in the supply chain. Furthermore, it allows feed manufacturers to secure their supply of raw materials and operate with lower capacities, service times, and production buffers. For these reasons, as increased feed prices have had the largest impact on animal growers' and feed manufacturers' margins, there is a clear ongoing need for the investment in how animal feed distribution to farms is managed. In such complex decision-making environments, it is common to employ simulation and optimization methods. On the one hand, optimization methods are employed to find optimal or near-optimal configurations for distribution plans. Often, the associated optimization models are based on some simplifying assumptions. These assumptions contribute to making the problem easier to solve, but at the cost of ignoring the real-life uncertainty that characterizes these systems. On the other hand, simulation approaches are also used to model and compare the performance of different system configurations in a variety of scenarios. With the increasing advances in computing hardware and software, simulation has become a 'first-resource' method for analyzing complex systems under uncertainty (Lucas et al. 2015). However, simulation approaches alone are not able to generate optimal or near-optimal distribution plans in scenarios with many possible configurations. Hence, it makes sense to consider hybrid simulation-optimization methods that combine the best of both worlds.

Real-life optimization problems are often *NP-hard* and large-scale in nature, which makes traditional exact methods an inefficient solution approach – at least in reasonable computing times (Juan et al. 2009). Thus, the use of heuristic algorithms to obtain high-quality solutions in low computing times is required

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FIGURE A.2: Cover Page of Raba et al. (2019).

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(81) Designated States *(unless otherwise indicated, for every kind of national protection available):* AE, AG, AL, AM, AO, AT, AU, AZ, BA, BB, BG, BH, BN, BR, BW, BY, BZ, CA, CH, CL, CN, CO, CR, CU, CZ, DE, DJ, DK, DM, DO, DZ, EC, EE, EG, ES, FI, GB, GD, GE, GH, GM, GT, HN, HR, HU, ID, IL, IN, IR, IS, JP, KE, KG, KH, KN, KP, KR, KW, KZ, LA, LC, LK, LR, LS, LU, LY, MA, MD, ME, MG, MK, MN, MW, MX, MY, MZ, NA, NG, NI, NO, NZ, OM, PA, PE, PG, PH, PL, PT, QA, RO, RS, RU, RW, SA, SC, SD, SE, SG, SK, SL, SM, ST, SV, SY, TH, TJ, TM, TN, TR, TT, TZ, UA, UG, US, UZ, VC, VN, ZA, ZM, ZW.

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**Published:**

— *with international search report (Art. 21(3))*

(54) **Title:** A METHOD AND A SYSTEM FOR ASSESSING THE AMOUNT OF CONTENT STORED WITHIN A CONTAINER

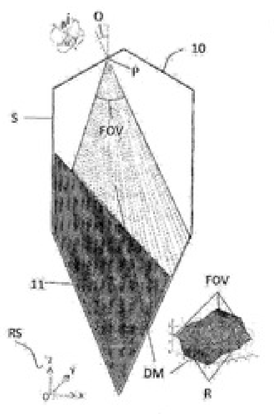


Fig. 1

(57) **Abstract:** The method comprising attaching a 3D sensor (20) on a top part of the container (10) in a position (P) and with an orientation (O) such that its field of view (FOV) is oriented towards the content (11) stored in the container (10); acquiring, by the 3D sensor (20), a depth map (DM); and computing, by a computing unit, a 3D surface model by processing said acquired depth map (DM) and using said given position (P), orientation (O) and field of view (FOV), and a 3D level model by removing from the computed 3D surface model the points corresponding to the interior walls of the container (10), using a 3D function that searches the intersection or matching between the 3D surface model and the shape of the container (S), and filling in the missing points corresponding to the content (11) that falls out of the field of view (FOV) of the 3D sensor (20).

WO 2017/137832 A1

Figure A.3: Cover Page of INSYLO patent (2018).

**Submitted to *INFORMS Journal on Applied Analytics***
**manuscript (Please, provide the manuscript number!)**

# A Digital Twin for Decision Making on Livestock Feeding

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This work is part of the IoFEED project, which aims at monitoring approximately $325$ farm bins and investigates business processes carried out between farmers and animal-food producers. A computed-aided decision system is proposed to control and optimize the supply chain to deliver animal feed to livestock farms. Orders can be of multiple types of feed and shipped from multiple depots by using a fleet of heterogeneous vehicles with multiple compartments. Additionally, some business-specific constraints have been considered, such as product compatibility, facility accessibility restrictions, prioritized locations, or bio-security constraints. A digital-twin based approach is implemented at the farm level by installing sensors to remotely measure the inventories. Our approach combines biased-randomization techniques with a simheuristic framework to make use of data provided by the sensors. Initially, two test-beds have been set in two distinct European countries, the United Kingdom and Spain. The analysis of results is based on these two real pilots with similar pains, and showcases the insights obtained during the IoFEED project. The results of this work show how the Internet of Things and simulation-based optimization methods are combined successfully to optimize the feeding operations to livestock farms.

*Key words*: vehicle routing problem, internet of things, animal farming, feeding, heuristics
*History*:

Livestock production in the European Union represents $40\%$ of the overall agriculture output. The European feed sector is of utmost importance to the livestock industry. Farm animals in the EU-28 consume an estimated $478$ million tons of feed a year, of which $163$ million tons are produced by compound feed manufacturers (FEFAC 2018). The European feed industry is a growing industry, with an estimated turnover at €$50$ billions, that directly employs approximately $110,000$ people, most of them in rural areas where employment offers are usually scarce. Even though most of the compound feed plants are small and medium enterprises (SMEs), they have an average production volume of $40,000$ tons of compound feed per plant (FEFAC 2019). The quality of this compound feed is really important to farmers, because it directly correlates with milk or meat quality. A better knowledge of the farm's nutritional needs gives the feed manufacturer the best position to plan raw material procurement, as well as give them a reliable supply chain,



FIGURE A.4: Cover Page of Raba et al. (2021). Submitted work on second review.

sensors MDPI

Article

# A Method to Compensate for the Errors Caused by Temperature in Structured-Light 3D Cameras

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**Abstract:** Although low cost red-green-blue-depth (RGB-D) cameras are factory calibrated, to meet the accuracy requirements needed in many industrial applications proper calibration strategies have to be applied. Generally, these strategies do not consider the effect of temperature on the camera measurements. The aim of this paper is to evaluate this effect considering an Orbbec Astra camera. To analyze this camera performance, an experimental study in a thermal chamber has been carried out. From this experiment, it has been seen that produced errors can be modeled as an hyperbolic paraboloid function. To compensate for this error, a two-step method that first computes the error and then corrects it has been proposed. To compute the error two possible strategies are proposed, one based on the infrared distortion map and the other on the depth map. The proposed method has been tested in an experimental scenario with different Orbbec Astra cameras and also in a real environment. In both cases, its good performance has been demonstrated. In addition, the method has been compared with the Kinect v1 achieving similar results. Therefore, the proposed method corrects the error due to temperature, is simple, requires a low computational cost and might be applicable to other similar cameras.

**Keywords:** RGB-D camera; camera calibration; temperature effect; structured light; infrared pattern distortion



**Citation:** Vila, O.; Boada, I.; Raba, D.; Farres, E. A Method to Compensate for the Errors Caused by Temperature in Structured-Light 3D Cameras. *Sensors* **2021**, *21*, 2073. https://doi.org/10.3390/s21062073

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## 1. Introduction

Three-dimensional (3D) shape measurements have become fundamental in many different applications including robotics, virtual reality, industrial inspection or autonomous navigation, just to name a few [1–5]. Different technologies were successfully implemented in the past decades to measure the 3D information of an object, however how to perform these measurements in an efficient, effective and precise manner is still an important focus of research. Among all the technologies that have been proposed, 3D imaging technologies such as stereo vision, structured light and time of flight are the most cost-effective [6]. For a comparison of red-green-blue-depth (RGB-D) cameras representing these three main technologies see [7].

In this paper, our interest is focused on the 3D structured light imaging technology. In this technique, a pattern is projected on a scene and is then captured with a camera from a different position. Since the captured pattern is deformed by the scene shape, the analysis of the disparity from the original projected pattern provides the depth information. As it is illustrated in Figure 1, the basis of this technique is triangulation. Particularly, the depth of a scene point $Z_p$ can be computed following the Equation (1) described in [8]

$$Z_p = \frac{Z_o}{1 + \frac{Z_o}{f \cdot B} d} \tag{1}$$



FIGURE A.5: Cover Page of Vila et al. (2021). Accepted work 12 May 2021.

# Appendix B

# The IOFEED Project

## B.1 Introduction

The internet of things (IoT) has a revolutionary potential. A smart web of sensors, actuators, cameras, robots, drones and other connected devices allows for an unprecedented level of control and automated decision-making. The project Internet of Food & Farm 2020 (IoF2020) explores the potential of IoT-technologies for the European food and farming industry (Verdouw, Wolfert, Beers, Sundmaeker, and Chatzikostas, 2017). This project is funded by the European Comission by the agreement No. 731884.

### B.1.1 Pilot Description

The present PhD work is part of the IoFEED project (https://www.iof2020.eu), which aims at monitoring approximately 325 bins and investigate business processes carried out between farmers and animal-food producers. Initially, two test-beds have been set in three distinct European countries, the United Kingdom (UK), Sweden/Norway region (SW&NW), and Spain (ES). The UK has two distinct partners (UK1 and UK2) with 25 bins each, while Spain has a single partner (ES1) with 50 devices. The third pilot has been spread into a large are that comprises Norway and Sweden countries with 50 devices. After this initial phase, the number of monitored bins will increase up to 175 more for the Spanish pilot. Two business processes will be put to test in this project, which will analyze their cost-benefit and cost-effectiveness: *(i)* business process 1 (BP1), focused on farmers; and *(ii)* business process 2 (BP2), focused on helping to animal-food manufacturers. BP1 aims at providing the best solution for farmers to achieve a seamless procedure to measure bins' stock. The goals are: to provide accurate real-time information for daily tracking of food consumption in the farm, to assess feeding costs, and to help the farmer to increase his / her feed conversion rate, including a reduction in stock ruptures. Additionally to BP1 benefits, BP2 aims to change the business strategy moving the workload balance of maintaining the food stock to the feed supplier, so they can handle and manage the correct and exact amount of food for each bin that covers their client needs (the farmer) while, at the same time, optimizing the supply chain cost (production, own stocks, product shipping / distribution, etc.).

The three partners have been selected for several reasons. They represent distinct business models with which the animal industry face the feed distribution. Free marked, Integrators, Cooperatives and Machinery suppliers to the agrifood sector, but all of them have in common that want to stop beating around the bush and push their animal feed distribution into the a new age. Although the initial proposal was presented with three actors, we currently have two new actors that were not considered in the proposal.

### B.1.2 Batallé Group, The Integrator

The Batallé Group is made up of companies that work across different phases of the pork production chain. Its business activities span the production of pigs of high genetic value and cured hams, and the marketing of cuts of meat for the global market. Batallé's main goal is to ensure the utmost quality and complete reliability in all its products. his is achieved through the professionalism of our team, and a genetic enhancement program designed to turn out homogeneous, high-quality meat products. Batallé strives for the pigs at its farms to be raised in a setting that meets all their physical, dietary and health requirements. Good facilities favour the animals' welfare, as do diets tailored to their age, high sanitary standards, and proper treatment of the animals by well-trained staff. Batallé feed provider is the company ESPORC. A producer of feed supplying Batallé. Founded in 2002 and nowadays part of the holding. Research and Innovation (R&I) are two basic pillars upon which Batallé's solid structure rests. Batallé has its own team of researchers working in close collaboration with scientists at various prestigious entities, such as IRTA, the University of Lleida, the Autonomous University of Barcelona, and the University of Gerona, among others. These projects frequently receive support from a large number of government entities at the regional, state and European levels. All R&D activities are coordinated in a vertical manner, taking into account the specific needs of the Group's different companies.

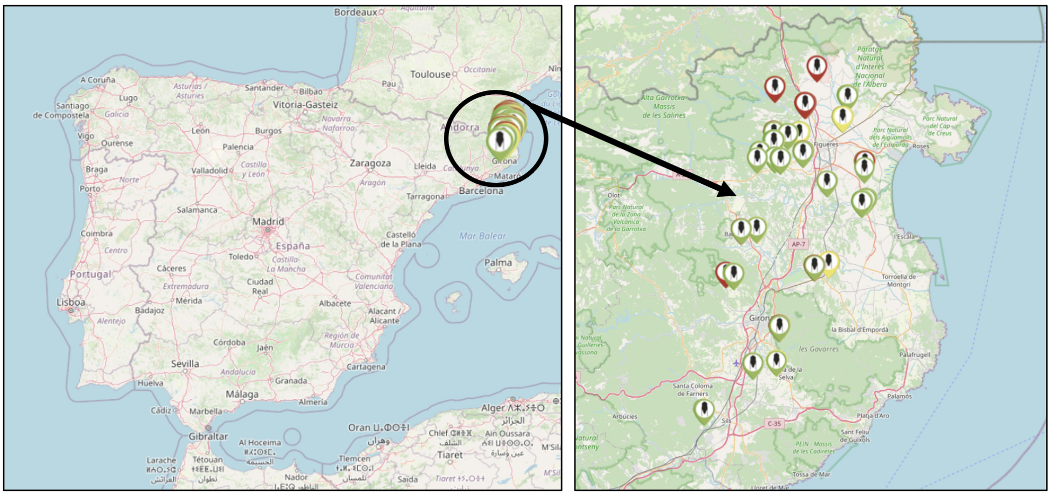


FIGURE B.1: Device design.

Batallé farms has provided a perfect test-bed for testing the sensors as well as develop the optimized feed distribution proposal. A set of 42 farms with 225 bins (Figure B.1).

### B.1.3 Dugdale Nutrition, The Feed Manufacturer

The origins of the business go as far back as 1850, when Mr John Dugdale was a tenant at Waddington Post Office. The property was purchased in 1854. John's son Benjamin joined the business and in 1880, the grocery and Post Office was expanded, retailing grains, oil cakes and by-products. These were delivered by train to Clitheroe and collected by the horse and cart. In 1892, the family became agents of Messrs J. Bibby & Sons, retailing their manufactured feeds. In August 2017, Dugdale Nutrition acquired 100% of the share capital of B Tickle and Sons Ltd. This acquisition brings together two family businesses with a combined 330 years' of trading history supplying the farmers of Northern England and beyond. With the manufacture of compound feeds at the Clitheroe site at 100% capacity, the acquisition of B Tickle & Sons Ltd allows extra manufacturing capacity, enabling the long term aim of both companies to deliver outstanding customer service. Dugdale Nutrition still remain a family owned business who have delivered innovation in the ruminant sector for over 170 years. With two production facilities running 24/7, we are proud to manufacture in excess of 250,000 tonnes of feed per year and have 24 dedicated vehicles out on the road delivering feed onto farm 363 days per year. This pilot has supposed 50 devices installed in 38 distinct farms (Figure B.3).

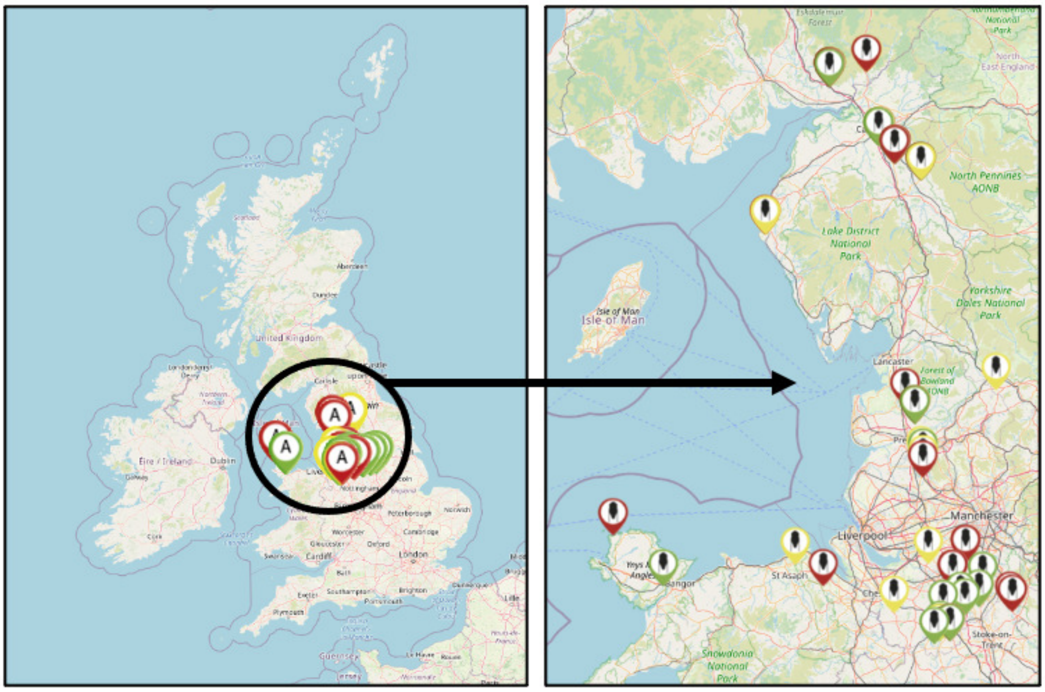


FIGURE B.2: Dugdale's pilot with 50 bins.

### B.1.4 Lantmännen Agro, The agricultural cooperative.

The company Lantmännen Agro is an agricultural cooperative and Northern Europe's leader in agriculture, machinery, bioenergy and food products. Lantmännen is owned by 20,000 farmers and with grain at the heart of our operations, they refine arable land resources to make farming thrive with operations in over 20 countries and an annual turnover of SEK 40 billion. The Agriculture Sector constitutes Lantmännen's core business and offers products and services to promote strong, competitive farming. The Agriculture Sector is based in Sweden, but also has a strong position in the Baltic Sea region through international ownership interests. International partnerships in plant breeding and feed development bring new expertise and research which is utilized and then turned into products that are adapted to Swedish farming conditions.

This pilot has involved the installation of 50 devices in a set of 28 farms located in the island of Gotland (Figure B.3). Lantmännen distributes feed to these farms and proposed the location due to its isolated nature with its difficulties to supply feeds regularly without the appropriate demand forecast.

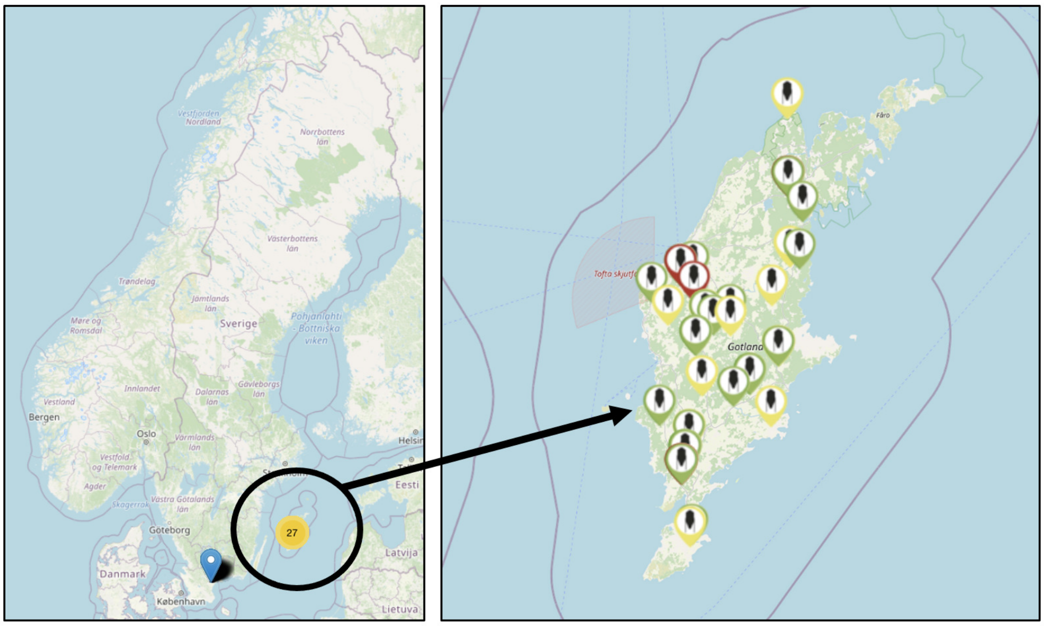


FIGURE B.3: Sweden pilot with Lantmännen Cooperative with 50 bins.

## B.2 Pilot execution

The COVID-19 pandemic, also known as the coronavirus pandemic, is still an ongoing pandemic of coronavirus disease 2019 (COVID-19) caused by severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2). It was first identified in December 2019 in Wuhan, China. The World Health Organization declared the outbreak a Public Health Emergency of International Concern in January 2020 and a pandemic in March 2020. As of 11 December 2020, more than 69.6 million cases have been confirmed, with more than 1.58 million deaths attributed to COVID-19. The lock-downs and restrictions on movement adopted in United Kingdom, Spain and other European and Eastern countries due to the COVID have affected our device manufacturing process, assembly and deployment, initially planned to start this early 2019. To the date, early January 2021, the device deployment has reached a total 60% of the initially planned deployment. Which has allowed us to achieve most of the goals of the IOFEED project.

## B.3 Lessons learnt and best practises

The proposed decision support system allows the distinct stakeholders to analyse alternative scenarios taking into account several target key performance indicators, such as distance, cost, number of routes, and truck utilisation. It is interesting to point out that during these pilots we have experienced some implementation barriers with farmers. They typically focus mainly on their core business, and have little or no interest in data gathering. Main concerns have been experienced in technological trustworthy, where "lack of trust" was perceived as a negative factor. Reliable technology is required to encourage farmers into low-risk implementations, even in the scenarios where they are not the facility owners. Although it is commonly accepted that smart farming requires information sharing across supply chains, farmers are still often not willing to provide access to their data in light of uncertainties about ownership and security concerns. While these concerns tend to dilute when they are not the real owners of the facility, the implementation of policies to give farmers ownership of their data will be required. All the actors of the value chain seek proven results of direct impact and improvement potential on individual farm and supply chain levels.

After this experience, we have learnt a lot. Mainly we have learnt about what not do. Next sections roughly mention some of them:

### B.3.1 About Sensor Network Deployment & Maintenance

- Hardware manufacturing is costly, risky and laborious; Setting clear goals, fail fast and gather feedback from field experiences as soon as possible helps a lot to minimise the pain. It is commonly known that sometimes doing things slowly, moves you faster to the finish line, especially when you are developing hardware from the scratch.
- Hardware deployment may be strenuous; Large scale pilots are not for everyone. One might be tempted to underestimate the effort required to deploy multiple hardware units spread across distinct countries and areas. It requires the appropriate preparation and validations. You are far from home, and you don't want to be there many times. So, be sure that your hardware is trustworthy before you deploy it far away.
- Hardware maintenance may be stressful and costly; So, you want to fail fast. Right, do it nearby, otherwise you will suffer a lot.
- Hardware is fun; Connecting the physical and the digital world is always satisfactory. Field work gives you a perspective from the world, impossible to guess from the lab. When your hardware it is going to be deployed in outdoor conditions, be sure to test them. Data-sheets helps a lot, but real world is wild.

### B.3.2 About Customer and Other Stakeholder's Relationship

- Be realistic with your sales pitches; Do not oversell. We are here to learn from them If they tell you that your product is not interested, trust them. You are probably talking to the wrong actor. Avoid pitching features until you succeed on convincing the wrong actor.
- Human beings are amazing; When you plan to build a service around your product, be careful with your number of clients. As many clients you have to deal with, as many issues you will have to solve. Identify a unique selling point and centralise the feedback from him. Dealing with too many human beings might be stressful and time consuming.
- Field work give you valuable insights; Again, dealing with the final users is always valuable. Even when they do start to disown your product. It is important to generalize a solution, you cannot make happy everybody.
- Agrifood sector is more tech-savvy as you may expect; We have seen a wide spectrum of situations. Things are moving and the sector is perfectly aware that digitalization is a must.

#### B.3.3 About R&D on Applied Optimization Algorithms for the Supply Chain

- Collaborate with pure Research teams gives perspective; When you are so focused on the real problem, with the real actors and the real daily routine, fresh, independent and carefree teams may help you to relativize the problems found in the battlefield.
- Get them on-board early; Although the project plan clearly organises each individual participation, having a partnership with them since the very first day has helped us a lot. It has allowed them to get the knowledge required to perform a shine when they have been required.

### B.3.4 About Business Case Implementation & Follow-up

- Clearly explain the project goals since the beginning; Rising high expectations is usually counterproductive. Partnering without sales prospects helps a lot to have a win-win relationship. We have enjoyed our journey with some of our partners. We still suffer the pain with others.
- Getting KPI is really hard; It is very difficult to set KPIs when you barely measure what is really interesting. Having the complete commitment from your industrial partner is a must. Otherwise, you will struggle a lot to measure something meaningful. Depending on their IT capabilities and their already set in place processes, this could be a titanic task.

### B.3.5 About Dissemination & Events

- You are not alone; Collaboration is great. If you find a clear alignment and set the basis for a healthy relationship the outcome may be impressive.
- I like coffee breaks; Try to take profit from the events, you never know who can you meet there. Maybe your next project/client/partner is waiting for you in the coffee machine.

### B.3.6 About Project Management

- Managing a project is relatively easy when uncertainty is under control. Contingency plans gain importance as problems arise. Also, flexibility and creativity on looking for solutions and alternatives are highly valued. We have experienced a bunch of everything in this project. It has help us to simplify the expectations.

## B.4 Project Proposal

Additionally, it is included in this annex the first four pages from the accepted proposal of the IOFEED project.

# 1. Cover page

## General details

| | |
|---|---|
| **Proposal Title** | IoT Supply Chain Platform for Animal Feed Industry |
| **Proposal Acronym** | IOFeed |

## Category

| | |
|---|---|
| **Category 1: New regions** | Yes |
| **Category 2: Post-farm stakeholders or other sectors** | Yes (Other sectors: Animal Feed Supply Chain) |
| **Both categories 1 & 2** | Yes |

## Coordinator details

| | |
|---|---|
| **Title (Mr/Ms/Mrs/Dr/Prof)** | Mr. |
| **First Name** | Jaume |
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| **SME** | Yes |

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Figure B.4: IOFEED Proposal - Page 1/4.

## 2. Proposal Description

The animal feed industry, mainly represented by feed suppliers and livestock farmers, suffer of great inefficiencies for both stakeholders. These inefficiencies are due to a very traditional and inefficient supply chain management, more precisely:

a) Bad estimations of feed stocks by farmers.
b) Uncertainty of feed demand.
c) Obsolete silo monitoring and restocking methods.

The **IOFeed** project aims at optimize the animal feed supply chain for global leaders and farmers by developing a cutting-edge integral feedstock management system ahead of any currently in the actual state of the art, and validate **two different business models**. The first business model will deliver and capture value **for the farmer**, and the second business model will change the business strategy delivering the value from the **feed supplier** point of view, introducing the concept of **Vendor Managed Inventories** (or **VMI**). Those two business models will be tested in three **(3) testbeds** that will be developed across three EU countries (ES, UK, DE), and will provide not only a validation of the scalability for future project results exploitation, but also of the market configuration, and the financial impact in the feed supply chain project participants.

The solution we propose to implement in this project is based on a ground-breaking 3D camera technology (**CLICK TO SEE VIDEO**) used to monitor the stock levels in the farms' silos, integrated with a Smart Feed Logistics Platform (SFLP) that will make use of leveraging IoT technologies as, Big Data, Artificial Intelligence (AI), and Cloud Storage to optimise the animal feed supply chain, benefiting both farmers and suppliers.

The animal feed is produced by the feed suppliers in the feed mills. Then it is distributed in bulk to different animal farms, where it is stored in silos. Each farmer requires a different composition of feed, which means that the feed supplier must prepare the feed ad-hoc for each specific farm and deliver it in a short period. Considering that each feed supplier is the provider for several silos from several farms (the top 50 EU feed suppliers manage on average 7,500 silos each), there is no doubt that the manufacturing and delivering process of animal feed is a key activity to be optimized. However, this feed supply chain is currently very traditional and inefficient: farmers have to manually check their silos every week to assess the stocks available and order the feed supplier to restock. Consequently, feed suppliers receive daily hundreds of refilling calls. Usually, they have only 24-48h to produce the feed, organize the delivery routes and hand it, which hinders completely the optimization of the whole process.

The main obstacle for developing a more efficient and automated feed supply chain is the lack of reliable and cost-effective solutions to remotely monitor the feed stock within a silo, what provokes:

a) Bad estimations of feed stocks by farmers: **i)** farmers run out of feed forcing costly urgent orders that break the production cycle of feed suppliers, **ii)** the silo is fuller than expected so trucks cannot fully unload the feed into the silo having to find an alternative location able to store it, **iii)** the silo is emptier than expected forcing more trips than necessary and preventing the optimal use of the trucks' load capacity.
b) Uncertainty of feed demand: **i)** feed suppliers cannot anticipate their coming orders, forcing them to produce on-demand in 24-48h, **ii)** feed production cycles and delivery routes cannot be optimised based on cost criteria, **iii)** purchases of raw materials cannot be optimised based on feed demand and market prices fluctuations.

Through an in-site market study carried out in several EU countries[1], it is calculated that the cost of this inefficiencies is of between 250 and 500 € per silo and per year (see Annex III). Since in the EU28 there are approximately 800,000 silos, **the EU28 sector's avoidable losses can equal up to 400 M€ per year**.

### 2.1. IOFeed project general description

The general objective of this project is to develop three testbeds in three countries, including two new regions regarding the IoF2020 initiative, in order to prove without any doubt: **a)** the technical feasibility of the proposed IoT solution using a sufficient amount of end-users and **b)** the return on inversion (ROI) of two new business models based on reformulation of animal feed value chain industry. This means digitalising the process of silo stock measurements, and allocating the feed supplier (VMI) with the responsibility to maintain the stocks

[1] Feasibility study funded by EC (Smart Agrifood project) + Pilot project funded by Vall Companys (top 3 ES feed supplier)

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Figure B.5: IOFEED Proposal - Page 2/4.

needed by the farmer while reducing the supplier's service costs. It is foreseen to automate and optimise: **1)** feed-stock inventories, **2)** production batches, **3)** delivery routes, **4)** raw material purchases and **5)** silos monitoring.

### 2.1.1. IOFeed project specific objectives

IOFeed project implementation will focus on three main project objectives:

1. Deploy and test three IoT-based Feed Supply Chain testbeds (2 small scale + 1 large scale)
2. Demonstrate proposed solution technological and economic viability.
3. Validate exploitation and scalability of the solution/project results.

By using this approach, we expect to cover the following IoF2020 Open Call specific challenges:

**Challenge 1. New regions: testbeds in 3 countries including 2 new regions**

The consortium is built upon the requisites to find the best partners to fulfil project objectives and widespread the results across EU member states and new regions with respect the actual IoF2020 configuration. Thus, the region of **Catalonia** in Spain and the region of **Bayern** in Germany will join the IoF2020 initiative as **new regions**, and the region of **South Western Scotland** in Scotland will also join the project.

**Challenge 2. Other sectors: optimising the animal feed supply chain.**

**Sub challenge 2.1. High impact of technical feasibility and innovation**

In this project we are going to test a novel IoT technology that allows, for the first time, the remote monitoring of the amount of feed contained in livestock farms' silos in a reliable and cost-effective way, solving all the identified drawbacks of current remote monitoring systems (high costs, lack of accuracy and difficult installation). This technology consists in a proprietary 3D camera with embedded computer vision algorithms that accurately assess the volume of the silo's content (see Figure 1). The IOFeed project aims at **validation of innovative INSYLO technologies and architecture** by deploying 325 devices in a group of farms, in order to collect a significant and relevant amount of data, and develop **new Business Intelligence (BI) tools** to help feed suppliers improve their performance and costs using AI-based algorithms, maximising the impact of the data collected and the interest for this kind of technologies in the sector.

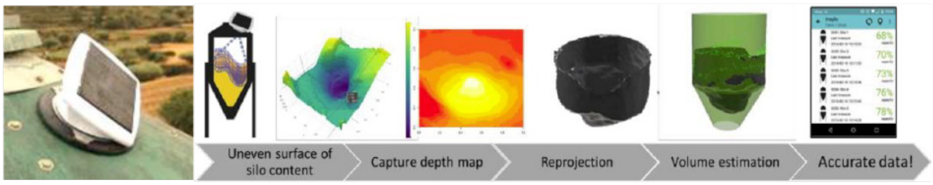


*Figure 1. IOFeed technology device (left), and measurement and data visualisation chain.*

**Sub challenge 2.2. Increasing impact in the Logistics and Supply Chain**

The IOFeed technologies will leverage the power of IoT, Big Data and Artificial Intelligence (AI) to collect vast amounts of information and solve the value chain's key question: when is the right moment and what is the right quantity to restock each silo, using a cost-effectiveness criterion and avoiding all the unnecessary labour, bringing together and benefitting farmers and feed suppliers as well. One impact is the concept of **Vendor Managed Inventories (VMI)**, in which farmer's inventory management and delivery route planning decisions will be taken centrally by the supplier instead of the farmer. This VMI concept will have an impact of **10% reduction in logistics costs** for the supplier (having an economic impact of 400 M€ in EU28), a **reduction of 22 days per year**[2] of silo monitoring labour, and a **reduction of 15% in CO2** production.

In this project we will monitor approximately 325 silos and validate two business models. In a first phase, we will implement three testbeds in each country (50 silos each) and validate business model 1 that will have impact in the farmer's inventory management, automatization of **stock monitoring** and **stock ordering**, and control of **feed consumes.** In a second phase, we will increase the number of silos with 175 more (only in the

[2] Impact in logistics costs and famer's labour reduction is based on INSYLO's project internal data done for the company *Vall Companys SA* (one of the top Spanish feed suppliers).



FIGURE B.6: IOFEED Proposal - Page 3/4.

Spanish testbed), and validate business model 2 that will have impact, from the supplier's point of view, in the **stock management**, feed **production batches**, optimisation of **shipping routes**, production lots, and raw material **procurement**.

**Sub challenge 2.3. Fast market uptake**

One of the main results of this project is the validation of two innovative business models (one taking care of the farmer's value chain and the other from the supplier's value chain), facilitating the adoption of new innovative models and the technologies deployed in the project. At the same time, the resulting product/service will **extend the IoT market place** opening new opportunities in other sectors with similar problems (cement silos, waste bins, etc.). On the other hand, if the results of the project are satisfactory, the participant feed suppliers have committed to deploy the technology to the rest of the silos that they manage (over 8,500 silos in total) and participate in the dissemination efforts to promote a fast adoption within the sector.

### 2.1.2. Work plan and activities

The project implementation and development will be broken down into the following work packages (WP):

- **WP1: Testbeds setup and deployment**. This WP will focus on manufacturing, firmware installation, quality control, and calibration of 375 INSYLO devices and on the installation of 325 of those in each silo of every farm that will be part of the three country testbeds. The remaining 50 devices will be used as spare parts for future maintenance. The INSYLO devices and monitoring platform setup will be deployed in the farms recruited by Batallé, BayWa and Davidsons in each region.
- **WP2: Validation of Business Model 1 (Farmer)**. Having the devices and the visualization tools installed, the first business model will provide feedback about how the IoT system is integrated into the every-day workload of the farmers, and determine what are the new system/model benefits. Specific KPIs will be defined for BM1 to prove real ROI. This BM will be implemented in all three regions.
- **WP3: Systems (Smart Feed Logistics Platform) Integration into feed suppliers' system and Development of new BI features**. This WP will focus on the integration of INSYLO control and monitoring tools used by farmers into the feed suppliers' information management systems. The goal is to test this integration within all the supply chain (logistics, stocks, shipping, orders management, ERP and CRM internal systems, etc.). Once the monitoring system is integrated, we will need to develop Business Intelligence features to optimise feed supplier internal procedures, and define security and privacy features based on WP5 defined KPIs with Cloud compatibility.
- **WP4: Validation of Business Model 2 (Supplier)**. In this WP we will validate the newly defined business model paradigm (Vendor Managed Inventories) so the feed supplier and the farmer have both improved their benefit and reduced their respective operating and management pains. Specific KPIs will be defined for BM2 to prove real ROI. Thus, this work package will focus on overall project evaluation (lessons learned) and the preparation of activities regarding the sustainability and replicability of the project achievements and results. This BM will only be implemented in the Spanish testbed.
- **WP5: Management, Dissemination, and exploitation for future perspective**. Coordination of different WPs with partners, reporting to the IoF2020 Consortium, resource allocation and financial administration, etc. Also developing after-project/project results exploitation plan and market analysis.

The project duration will be of about 24 months with the following implementation work plan:

| | 2019 | | | | 2020 | | | |
|---|---|---|---|---|---|---|---|---|
| | Q1 | Q2 | Q3 | Q4 | Q1 | Q2 | Q3 | Q4 |
| WP1. Testbeds setup and deployment | ■ | ■ | ■ | ■ | | | | |
| WP2. Validation of BM 1 (Farmer) | | | ■ | ■ | | | | |
| WP3. Systems Integration and new BI features | | | ■ | ■ | ■ | ■ | | |
| WP4. Validation of BM 2 (Supplier) | | | | | ■ | ■ | ■ | ■ |
| WP5. Project management, dissemination, and exploitation | ■ | ■ | ■ | ■ | ■ | ■ | ■ | ■ |

Deeper description of each WP and their corresponding tasks, objectives, lead partner and duration:

| Work package number | WP1 | Start Date or Starting Event | M1 – M12 |
|---|---|---|---|
| Work package title | Testbeds setup and deployment | | |
| Name of participants (leader) | **INSYLO**, BATALLÉ | | |
| Person/months per participant: | INSYLO (3.4), BATALLÉ (1.0) | | |
| OBJECTIVES | | | |

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FIGURE B.7: IOFEED Proposal - Page 4/4.

# Appendix C

# Feed Planning

## C.1 Introduction

Profits in livestock industry come from the margin between the price paid for the carcass and the costs that are incurred to produce it. The major production cost is the feed. The more food required to produce a kilogram of meat, the less the profit. The genetic make up of the pig is vital in this respect: 10 kg of feed produces approximately 8 kg of lean meat and 2.5 kg of fat (Cutler, 2014). Therefore, an animal that can convert more of its feed into lean meat is much more profitable than one that transforms it into fat, however, this obvious factor is frequently neglected. The rate of deposition of lean meat is dependent on the sex of the animal, its genetic background, the type of feed used, the quantity fed, as well as diseases and their effects on the growth rate. Excess fat at slaughter may be severely penalized. However, a lean pig is more susceptible to environmental change and diseases. During the past two decades, in many pig producing countries across the world, there has been considerable emphasis on the selection of pigs with high lean tissue deposition that will continue through to the slaughter weight. In the past, the unimproved pig maximized its lean tissue growth at around 40 kg. The current pig maximizes its lean tissue growth at the expense of fat at $60 - 90$ kg. The best sires available, i.e.: those with rapid growth, good feed conversion efficiency, good killing out percentage or yield, and high levels of lean tissue deposition are always used (Cutler, 2014). All these traits are highly heritable. The business process modeling is the representation of the activities of the business processes of an organization to be analyzed and improved.

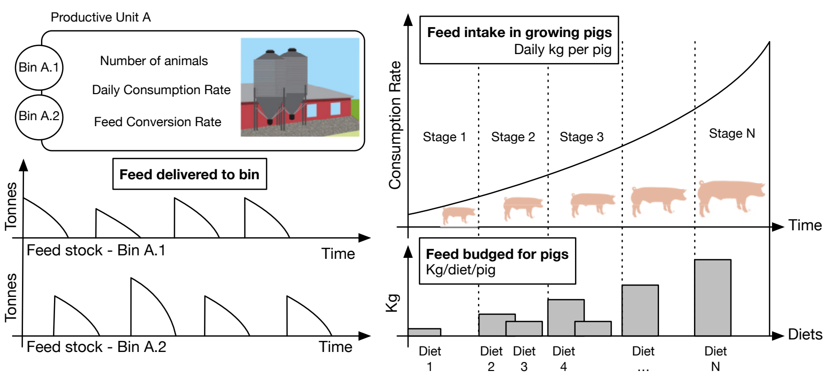



FIGURE C.1: Fattening pig has an intensive diet to maximize its growth at the best cost.

Having this in mind, Figure C.1 depicts a typical small farm, where feed delivery follows a precise plan despite its small scale. This plan is specifically tailored to the animal breed and its growing stage. The farm facility stores feed into bins, and this feed is consumed with a certain consumption rate, which depends on the number of animals and its stage. The bulkiness of a feed determines the amount that a pig can consume to achieve gut fill. This is the major cost component of growing a pig, i.e., feed intake and efficiency can be increased through a suitable delivery process (Schinckel, Mahan, Wiseman, and Einstein, 2008). In order to increase the profitability, specific feed intake curves are set according to the animal growing phase.

The optimization of pork production systems requires knowledge of pig feed intakes, growth rates (average daily gain or ADG), estimated measures of feed (average daily feed or ADF and feed/pig ratio), and energetic efficiency to set the appropriate dietary management. Table C.1 shows a sample feeding program for fattening pigs, specifically tailored to the type of farm. Given a starting pig weight, it describes the expected quantity intake per pig until the market weight (Mkt) is reached. It also quantifies the expected weight gain per animal, as well as the distinct diets to be consumed sequentially. In that sense, providing the appropriate diet at a precise moment of the fattening process is of utmost importance. Those decisions must be considered when deliveries to farms are planned. Only by doing that it is possible to decrease costs in transport and in-farm logistics (bin clearance, remaining feed removal, etc.).

TABLE C.1: Sample feeding program for fattening pigs.

| Diet name | # Diet | Pig wt. (kg) | Pig age (days) | ADG (g) | ADF (g) | Feed: Gain | Feed/pig (kg) |
|---|---|---|---|---|---|---|---|
| Starter 1 | 101 | 6.2 to 14 | 19 to 14 | 115 | 125 | 1.1 | 5 |
| Starter 2 | 102 | 14 to 35 | 29 to 72 | 765 | 1,225 | 1.6 | 50 |
| Grower 1 | 201 | 35 to 65 | 72 to 104 | 920 | 2,300 | 2.5 | 80 |
| Finisher 1 | 301 | 65 to 95 | 104 to 136 | 930 | 2,950 | 3.4 | 110 |
| Finisher 2 | 302 | 95 to Mkt | 136 to 159 | 830 | 3,000 | 3.6 | 60 |

Nowadays, big corporations are investing to narrow this gap as they recognize that planning the feed logistics from the factory to the farm is essential to: *(i)* protect the feed as much as possible; and *(ii)* increase the business profitability (Cutler, 2014).In the next section C.2 we describe the context of the problem we aim to solve.

## C.2 Materials and Methods

The efficiency of use and the nutritional value versus price are very important indicators. How it is delivered and made available to the pig can increase feed intake and maximise feed efficiency. The Spanish business partner follows specific feeding curves to plan feed deliveries.

Figure C.2 depicts a sample feeding curves used by the company. A feeding process follows distinct stages, for instance, a first stage used to adapt the animals to this location, while animals eat feed recipes specifically tailored to their growing stage. Hence, for a given stage, and an animal breed (ie. pigs breeds like Duroc, American Yorkshire, Basque, Berkshire, etc.), this table define an ordered list of recipes to be consumed during this stage. According to nutritional advice, a set of feeding profiles can be used (shown in

| | | | | | | PROFILES | | | |
|---|---|---|---|---|---|---|---|---|---|
| STAGE | ANIMAL CLASS | CODE | NAME | MANUFACTURER | OBS | 101 | 102 | 103 | 104 |
| STAGE 1 | CLASS A | 035263 | MATERNAL A | LOCATION A | ... | x | x | x | |
| | | 035264 | MATERNAL B | LOCATION A | ... | | | | x |
| | | 128939 | PRESTARTER A | LOCATION A | ... | | | 3 | 3 |
| | | 128940 | PRESTARTER B | LOCATION A | ... | 3 | 3 | | |
| | | 237380 | STARTER A | LOCATION A | ... | 15 | | | 15 |
| | | 237381 | STARTER B | LOCATION A | ... | | 15 | | |
| | | 237382 | STARTER C | LOCATION A | ... | | | 15 | |
| | | | | | | 102 | 105 | 107 | 108 |
| STAGE 2 | CLASS A | 310001 | GROWER A | LOCATION A | ... | 180 | 180 | | |
| | | 310011 | GROWER B | LOCATION A | ... | | | 195 | |
| | | 310023 | GROWER C | LOCATION A | ... | | | | 200 |
| | | 456701 | FINISHER A | LOCATION A | ... | 70 | | 80 | |
| | | 456703 | FINISHER B | LOCATION B | ... | | 90 | | |
| OTHERS | CLASS A | 801021 | MEDICATED A | LOCATION B | ... | 50 | 80 | 80 | |
| | | 801075 | MEDICATED B | LOCATION A | ... | | | | 80 |
| | | 801340 | MEDICATED C | LOCATION A | ... | 5 | 5 | | |
| | | 801589 | MEDICATED D | LOCATION B | ... | 15 | | | |

FIGURE C.2: Representation of our real-life problem.

Figure C.2 as 101, 102, 103 for stage 1, under Profiles header). Once profile number is selected to follow, specific weight to be consumer per animal is suggested (precise Kg per animal to be consumed or unity indicated with a cross when is delivered under commercial package).

Figure C.3 shows a sample run of the feeding curves where two stages are followed for a given animal class A. Codes for the feeding curves used are 101 for the stage 1 and 105 for the stage 2. Planned facility is considered to feed up to 300 animals with a bin storage capable to store up to 12000 tones of feed.

**Example:**

| Breeding | | | Facillity | |
|---|---|---|---|---|
| Animal Class | | A | Shed Capacity | 300 animals |
| Stage 1 | Curve Num. | 101 | Bin Capacity | 12000 Kg |
| Stage 2 | Curve Num. | 105 | | |

| Delivery Plan | | | | | | | |
|---|---|---|---|---|---|---|---|
| Date | Diet Code | Diet Name | Dose | Daily Consumption | | Quantity | Livespan (days) |
| 01/10/2020 | 035263 | MATERNAL A | 1 units | - | - | 1 units | 1 |
| 02/10/2020 | 128940 | PRESTARTER B | 3 kg | 1,4 kg | | 900 Kg | 2 |
| 04/10/2020 | 237380 | STARTER A | 15 kg | 1,9 kg | | 4500 Kg | 8 |
| Date | Diet Code | Diet Name | Dose | Daily Consumption | | Quantity | Livespan (days) |
| | 310001 | GROWER A | 180 kg | SPLITTED | 4,5 | 54000 Kg | 68 |
| 12/10/2020 | 310001 | GROWER A | | 2,2 kg | | 12000 Kg | 18 |
| 30/10/2020 | 310001 | GROWER A | | 2,4 kg | | 12000 Kg | 17 |
| 15/11/2020 | 310001 | GROWER A | | 2,8 kg | | 12000 Kg | 14 |
| 30/11/2020 | 310001 | GROWER A | | 3,1 kg | | 12000 Kg | 13 |
| 13/12/2020 | 310001 | GROWER A | | 3,2 kg | | 6000 Kg | 6 |
| Date | Diet Code | Diet Name | Dose | Daily Consumption | | Quantity | Livespan (days) |
| | 456703 | FINISHER B | 90 kg | SPLITTED | 2,25 | 27000 Kg | 28 |
| 19/12/2020 | 456703 | FINISHER B | | 3,3 kg | | 12000 Kg | 12 |
| 31/12/2020 | 456703 | FINISHER B | | 3,2 kg | | 12000 Kg | 13 |
| 12/01/2021 | 456703 | FINISHER B | | 3,1 kg | | 3000 Kg | 3 |

| Leadtime | Start | End | Total Feed | Days |
|---|---|---|---|---|
| | 01/10/2020 | 16/01/2021 | 86401 Kg | 107 |

FIGURE C.3: Example of a Material Requirement Planning (MRP).

Curves exemplified in Figure C.2 are used to run a classical Material Requirement Planning process (MRP) where products to be delivered are identified as well as quantities according to the number of animals. Bin capacity is used to split large demands of a single product, meeting capacity and lifespan stock constraints. Specifically, and following the MRP plan, first row indicates a planned delivery of a diet code 035263, one unit per animal. This product will last for one day. For the 12$^{th}$ October it is planned an partial delivery of 12 tones (diet code 310001 of 180 Kg per animal, 54 tones in total per shed). This order is expected to last 18 according to the empirical 2.2 Kg of average daily consumption rate per animal. Hence, it is possible to forecast the orders to be placed during this production period. As a resulting, it is expected feeding period of 107 days with a total consumption of $86,401$ Kg of feed.

## C.3 Consumption Rate Estimation

Initially, an experimental intake rate is used to estimate stock lifespan. Even though, during the feeding process more precise estimations are applied as every bin storage is equipped with sensors to accurately measure the real stock levels. Hence, lifespan estimations can be dynamically updated by using real intake rates according to the measure daily consumption and the number of animals in shed.

## C.4 Results

The adoption of these feeding plans with the knowledge of the farm facility, in terms of layout utilization (bins, sheds and its association, number of animals, etc.) enables the system to compute an estimated MRP. This plan may consider average consumption rates, limitation on maximum number of days while the same feed is stored at bin to promote the feed freshness, etc. This information allows us to place the orders in advance (ready to be confirmed), depending on how the real consumption is measured by the sensors. Planification may be adjusted to match the real consumption and the variation on breed quantities.

Hence, Figure C.4 shows the planned orders, quantities and recipe type estimated according the initial constraints. It manages the distinct stages managed by the feeding plans and the available capacity at farm.

Figure C.5 depicts the whole feeding period as it is being planned initially. With the integration of the sensor network, it will be adjusted to match the real consumption trends.

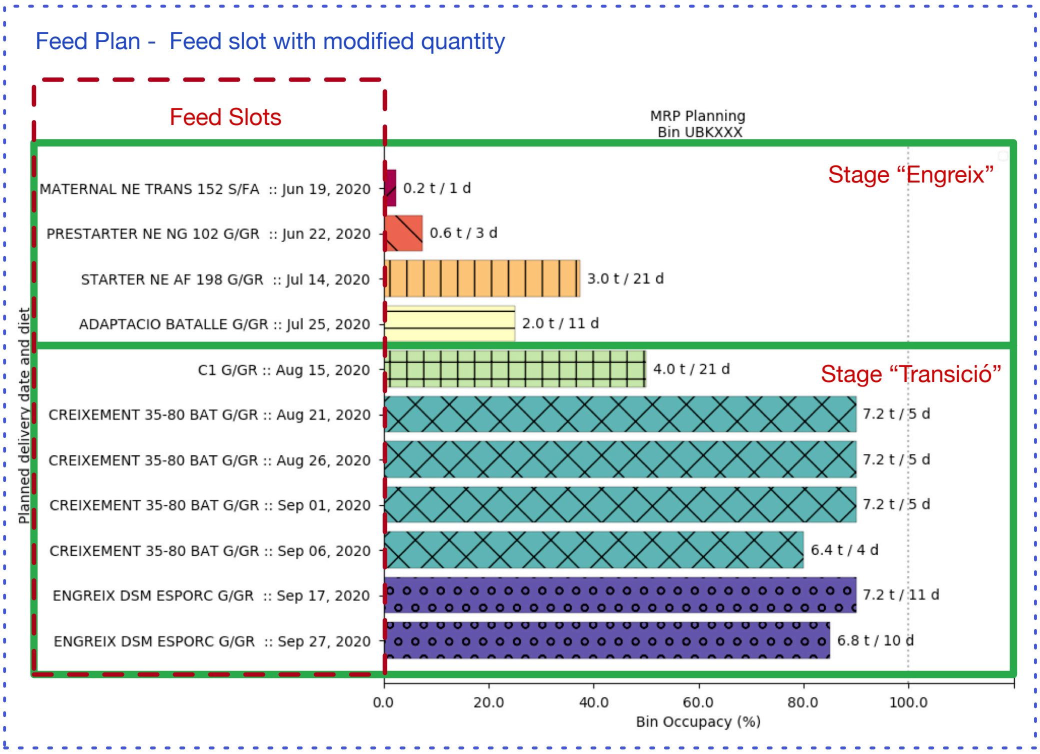



FIGURE C.4: Representation of our real-life problem.

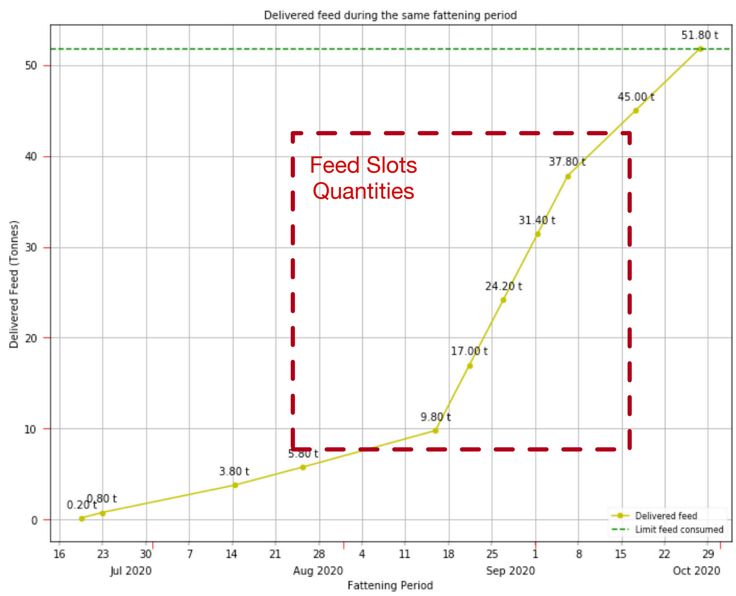



FIGURE C.5: Representation of our real-life problem.

# Appendix D

# The INSYLO Company

## D.1 A hardware as a service business

There are two main kind of solutions in the market that have attempted to provide a solution to remotely monitor feed stocks in livestock farms silos: They either measure silo's weight or measure the feed level inside the silo. The first approach (weight) uses "load cells", which are installed in the silo's support structure. The second approach (level) uses level sensors usually based on cable, radar, ultrasonic or guided wave technology. To access the data remotely, they often use standard data loggers and GSM modems with private protocols. Although these kind of technologies have gained market in several industrial applications, they have failed to do so in the livestock sector due to the special requirements that a solution must fulfill to be widely adopted: cost-effectiveness, accuracy and suited for rural environments. Hence, their market share is lower than 1%.

Figures D.1 and D.2 show the designed version of the sensor with its IP67 enclosure and the current hardware platform with which INSYLO controls feed inventories stored in farms. With a simplified methodology for installing this sensor and the proper sealing for avoiding water leakage into the bin, this sensor allows INSYLO to accurately measure inventories of bulk solids stored in bins.

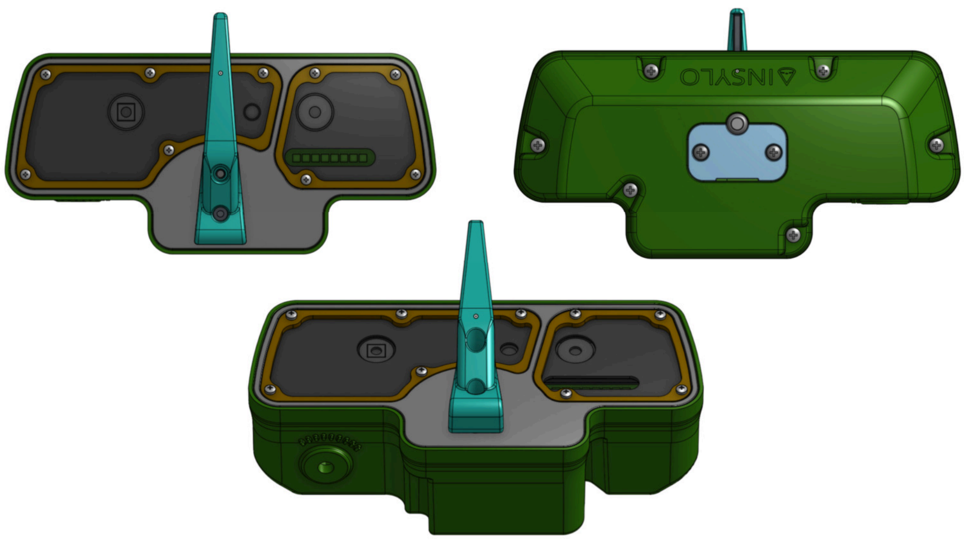


FIGURE D.1: Last device sensor design with the double camera RGB and depth sensor, and the cleaning system.

The general goal of the thesis is to develop INSYLO's commercial version (to shift from a TRL7 to a TRL9) and to establish commercial agreements with our target customers,

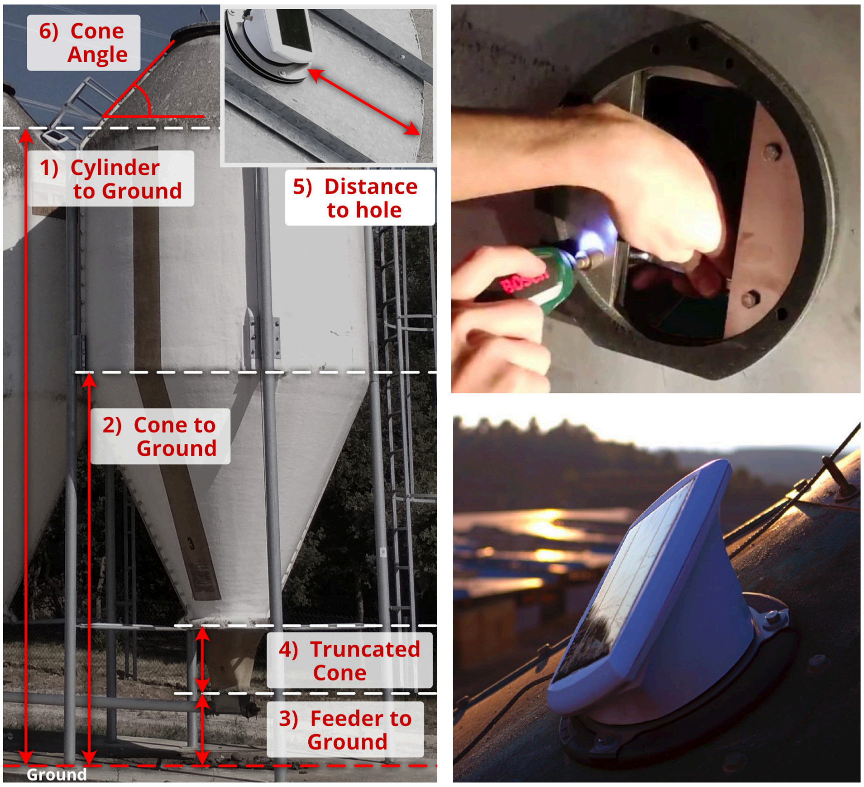



FIGURE D.2: Installed device on top of the silo.

to foster a fast market uptake when we launch our product to the EU28 market in 2021. To attain this aim, we have set the following specific goals based on the Feasibility Study insights:

- To optimise the camera's algorithms, ensuring reliability and reducing computing time and data packed size to save the energy consumed and reduce the transmission costs.
- To develop firmware update capability through OTA (over-the-air) to ensure the stability of the devices network and allow remote camera's software update.
- To refine Web/Mobile App Graphical User Interfaces + new features implementation.
- To implement service & customer support tools.
- To test and fine-tune the Smart Logistics cloud platform and assure a reliable service able to cope with more than 500K sensor points.
- To industrialize the manufacturing process to maintain the device's production costs below EUR 150 once Economies of Scale applies.
- Customers' engagement for a successful market uptake: to build a clients' network with the largest EU feed suppliers.
- To build an authorized dealers' network to boost the scope of our commercial action.
- To obtain Electromagnetic Component Certifications required to market INSYLO in our target countries (EU28-CE, US-FCC, China-CCC, Brazil-INMETRO).
- To protect the IPR, reviewing the patent already filled and filling new ones to protect the innovations developed during Phase II.
- To gain market visibility among our target users through communication and dissemination activities.

### D.1.1 State of the art

According to talks with silo manufacturers and installers of farms, only 5% of new farms are equipped with silo monitoring systems. The figure for old farms is almost negligible. The main system used are load cells that have the advantage of accurately measuring weight, but most customers choose not to install them because of their high cost. The approximate installation cost is EUR2,500 per silo. However, some Asian suppliers have started to appear with prices around EUR1,500 per silo. There are similarly-priced alternatives on the market that offer level measurement using cable, ultrasound, radar and laser sensors, etc. These systems are installed on top of the silo and have the drawback of a lack of precision. Indeed, measuring volume on solids is often a challenge due to material properties. There can be high peaks and deep holes and the surface is generally quite uneven. Using only a single device suitable for level measurement can often mean less accurate results and an inferred volume reading, since the volume will be based on the level reading from a small portion of the surface (ie. traditional level measurements like yo-yos, paddle wheels, etc.). Ultrasonic level measurement technologies do not provide the reliability or accuracy that is required for material management in grain. Figure D.3 summarises the competitors, technologies used and our competitive advantage.

| | INSYLO | lindcom | BINSENTRY |
|---|---|---|---|
| METHOD | VOLUME | WEIGHT | LEVEL (LASER) |
| ACCURACY | ✓ HIGH (error <3%) | ✓ HIGH (error <3%) | ✗ VERY LOW (error = 15-20%) |
| INSTALLATION | ✓ EASY (only 15 min) | ✗ VERY DIFFICULT | ✓ EASY (only 15 min) |
| CONNECTIVITY | ✓ INTEGRATED | ✗ STANDALONE MODULE | ✓ INTEGRATED |
| POWER | ✓ SOLAR | ✓ MAINS | ✓ SOLAR |
| MAINTENANCE | ✓ NO NEED | ✗ RECALIBRATION | ✓ NO NEED |
| PLATFORM | ✓ SMART LOGISTICS | ✗ ONLY DATA SERVICE | ✗ ONLY DATA SERVICE |
| PRICE | ✓ AFFORDABLE (<500€) | ✗ TOO EXPENSIVE (>2.000 €) | ✓ AFFORDABLE (< 500 €) |

FIGURE D.3: INSYLO benchmark with weighting cell as reference.

Many of the products found in the silos adhere to the sides causing product build-up and "worm holes" when entering. Only a 3D surface map of the interior of that vessel, which is a more accurate representation of the contents of the tank, can identify this issue with certainty. Advanced radar based sensors exist like 3D Multivision by Binmaster or Rosemount 5708 3D by Emerson. While these devices are overkill solutions in large silos (vessel height larger that six meters and three meters diameter), they fail on measuring small silos used in farms. Hence, these are not technically feasible in farm silos, neither by price nor installation costs.

Another method is to use 'load cells' that are installed underneath the silo. These literally weigh the amount of food remaining in the silo, but have a huge drawback in that the system needs to be installed before the silo is fixed in place(or by removing it and then retro-fitting). The cost of this installation is far too high to allow a farm to monitor any more than a handful of their silos. Generic suppliers of such load cells are: Thames Side, UTILCELL Load HBM, M Toledo, Alfer, Sensy, Laumas Elettronica, Georg Büttner, etc. These suppliers work within various large scale industrial environments with the farm feedstock sector and its small distributed silos, not at all being their core product, nor target market.

Another type of player offer's comprehensive solutions for monitoring silos sometimes through combining load cells with level sensors and a rudimentary communications system that sends data to a server. The cost of these systems is still high, but they have the advantage of making it possible to consult data from vendor-supplied software. Some suppliers of this type are: Sembra Technology Consulting, Anybridge, Leca, Apm Solutions, Fine-Tek, Cultura Technology, etc.

## D.2 Software

The development process at INSYLO follows Agile principles. That means looking for value at every loop while identifying the users' needs and anchor the quest for solutions to the appropriate problems. We apply those principles by implementing the so-called "Venture Design process (El-Awad, 2019). The VDP helps you know where to focus. Following the Figure D.4, it offers a systematic execution of continuous design and delivery that helps us focus on the right things at the right time, leveraging the best of what's out there in modern practices like design thinking and Lean Startup.

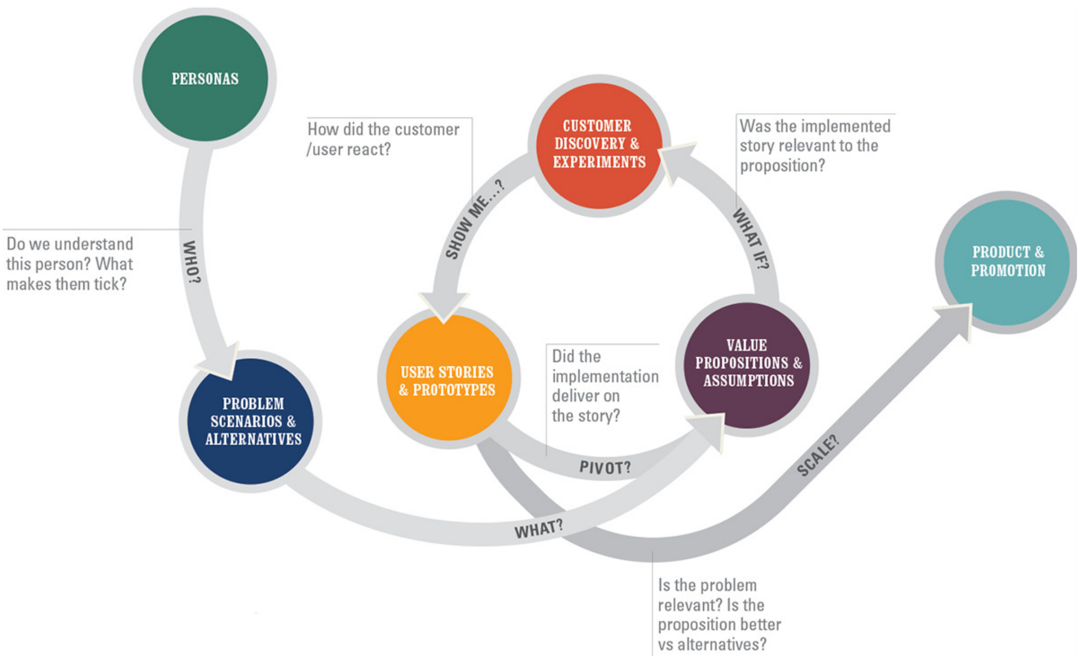



FIGURE D.4: Venture Design Process.

One of the first steps of every development is Persona identification. Essentially, getting a better understanding of the customer to identify what might have a real interest to be solved by build storyboards around the users' needs. Afterwards, we look for an accurate description of what needs to be done. If a problem scenario exists, the user is doing something about them now. By understanding those alternatives, we can build a better solution around it. Once we have identified the scenario to be solved, we need to ensure the key assumptions of our value proposition. We try to avoid building something nobody wants. We need to formulate clear KPIs around the solution we are creating to measure objectively how valuable it is. Next, experimentation is important to discover and test new concepts of what to build through interviews or usability tests. Prototyping around a user story allows us to align our product/feature development investments Alignment with the Personas & Problem scenarios are particularly important. The User Stories make for a great transition point and the practice of prototyping help us think through what we "really" have in mind. And finally, we face the final fully functional product/feature implementation after iterating on the value proposition, customer discovery and prototyping loop. We do not forget to enable actionable analytics that measures KPI around. It will allow us to set a reference baseline to compare within further improvements.

### D.2.1 Backend services

In this part, an architecture overview of the full system is given. The idea is to identify the different parts of the system as Figure D.5 shows.

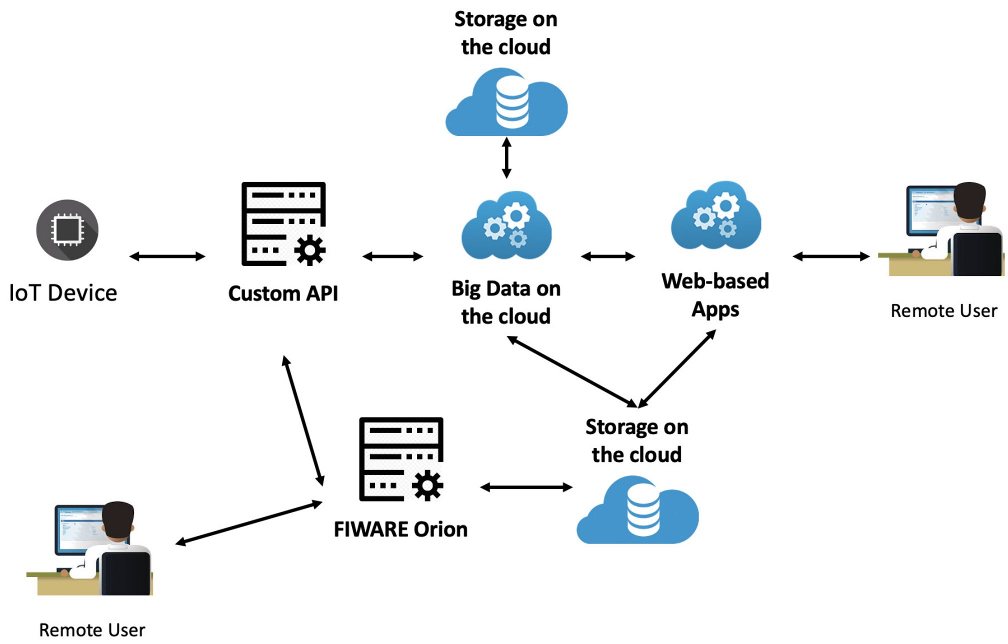



FIGURE D.5: STRIDE Analysis Level 0.

The system relies on an IoT device capable of sending measured data to the cloud services. A custom API receives a data packed in an hourly based sampling schema. This API internally redirects RAW data into a processing pipeline that estimates volume and weight using the bin's geometry and the measured depth map. This information is stored in internal and external services to provide the proper data to our applications. An API is exposed to the users to retrieve telemetry at bin level including weight, volume, temperature, humidity, battery, solar contribution, and other hardware information. All this information helps to maintain a healthy sensor network. The basic data model our API exposes follows the next diagram (Figure D.6).

The data model is essentially BIN centered. Data associated to a bin can be provided by several devices. Every data point linked to a bin can have a recipe assigned to it, so it is allowed to set multiple recipes for a given period of time. A bin is assigned to an area. Users are allowed to perform operations on a set of areas. One user belongs to a group. Each group has a permission schema where allowed operations are defined.

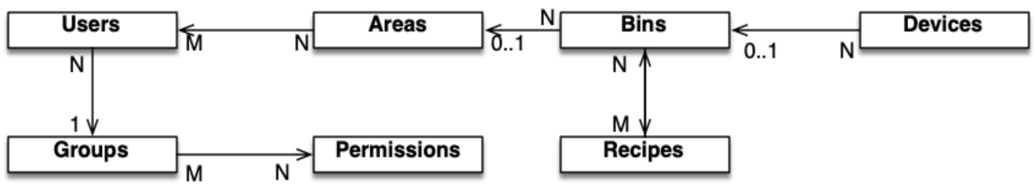



FIGURE D.6: Basic API entities exposed.

These entities are exposed by distinct API endpoints. By grouping those entities we have:Groups, permissions and units, Accounts, Client, and Auth, Devices, Areas, Bins and Recipes. Groups, Permissions and Units define a set of magnitudes of measurement (density, volume, weight, etc.) to be used in our platform. A set of groups are defined as well as the list of permissions that are used to segment what a certain group can or cannot do. Accounts, Client, Auth expose our API and allow to manage user creation, area visibility and authentication via TOKEN. Our user definition defines two distinct users. First, and admin user associated to each one of our clients, and the rest of the users a client can create itself that are linked to his admin user. Visibility rules are based on areas. Hence, each admin user can see and perform full operations on areas / bins linked to him. Every user created by this admin user behaves as defined in the group this user belongs to. User creation by using this principles, promotes scenarios where some users could have access to certain areas, and other users that only perform operations into a single area.

çInitially, as it was mentioned in the project proposal, FIWARE Stack has allowed to deploy a nearly full IoT stack. Generic Enablers' development and technical support team is easy to reach and to communicate with. NGSI adoption has helped us a lot to standardise the application context and organise the information of the productive environment with which we operate. Being open source, it has allowed to develop customizations on top of their proposals.

Due to product requirements, we moved from the gateway in-farm version into a GPRS-only version. Our microservice architecture has been simplified as well(Figure D.7).

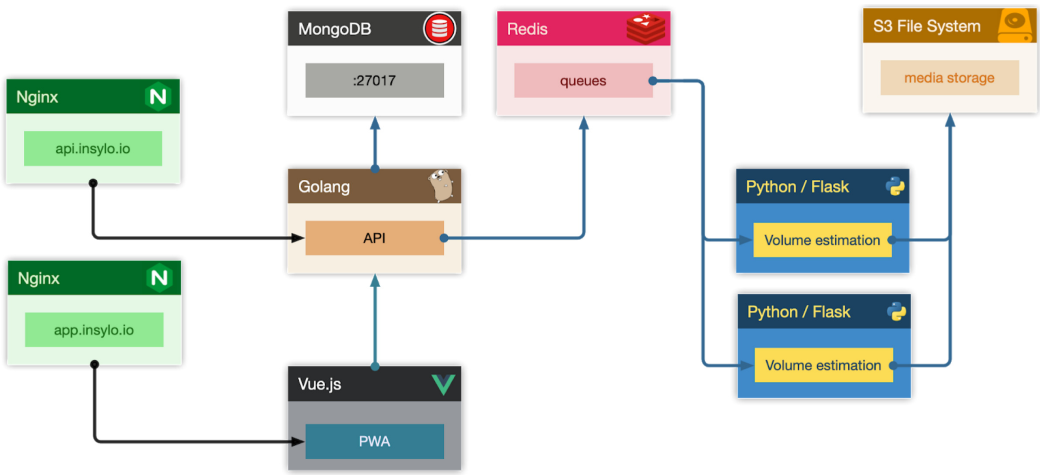



FIGURE D.7: Microservice architecture.

## D.2.2 Remote monitoring system

This section reports describing interfaces and tools implemented to integrate the Smart Feed Logistics Platform and the BI algorithms into the suppliers' IMS (ERP, CMS, Logistics system, etc.). The client app allows the user to operate our data service with the limited query operations of: List areas, list bins, set recipes/material/diets, create diets, assign diet to data point, plot RGB images, plot depth maps, plot bin/areas location and manage basic user data as password modification (Figures D.8-D.12).

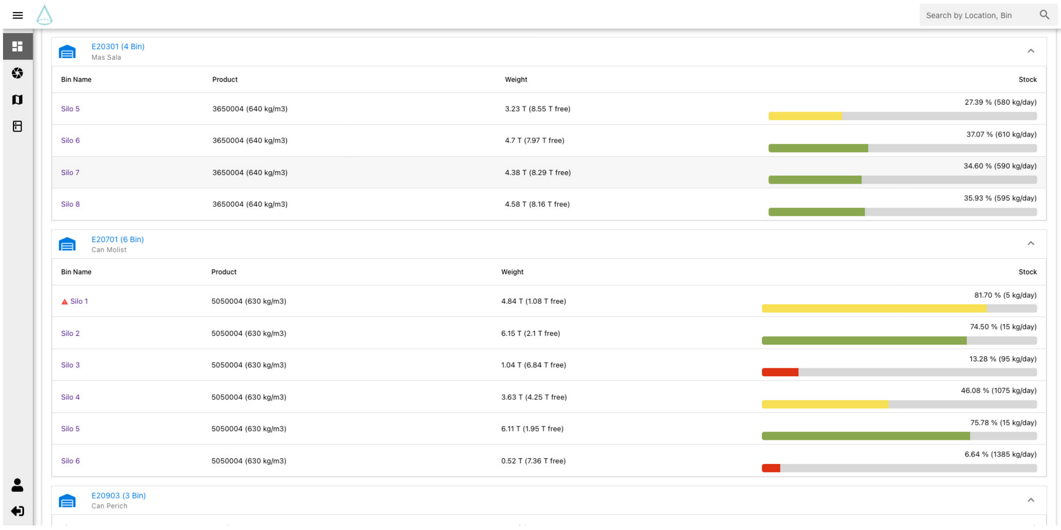



FIGURE D.8: Application landing page: Dashboard.

This client app makes use of the API, available to access by using the same credentials (user/password). This API exposes an extended list of operations, including: Creating new areas, bin relocation into areas, device management, device to bin linking, user creation, user permissions and group definitions, etc.

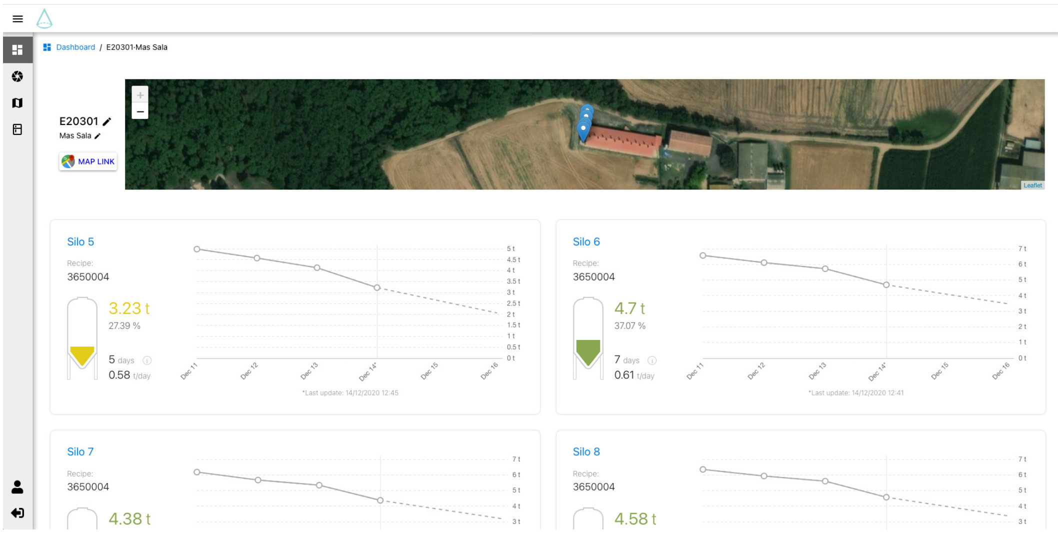



FIGURE D.9: Application Bin details status, RGB and timeseries.

## D.2.3 Technology Readiness Level

The INSYLO system has evolved from an initial TRL 1 to the current TRL 8, where the system prototype has been demonstrated in operational environment and it is being

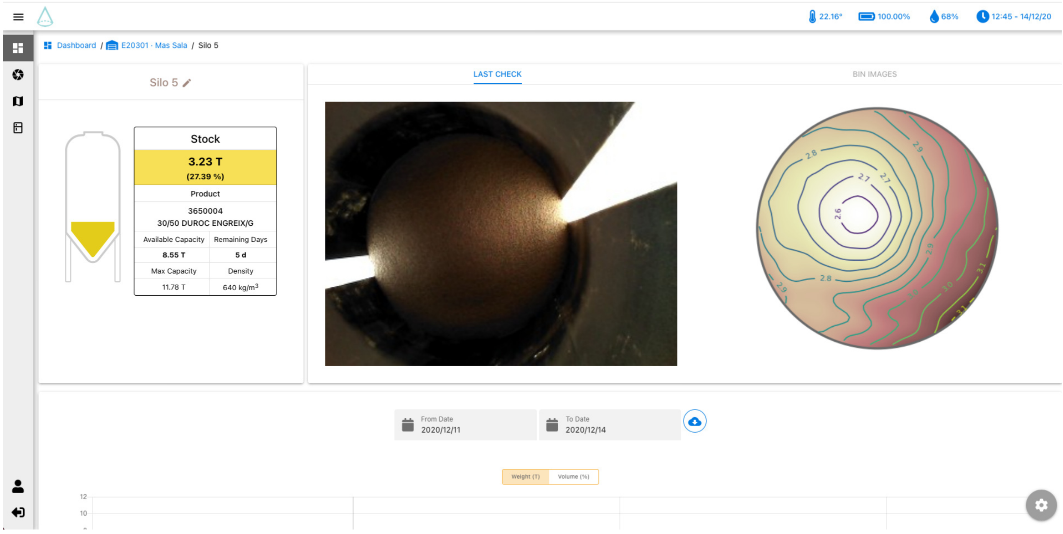



FIGURE D.10: Application: Weight, temperature and humidity time-series.

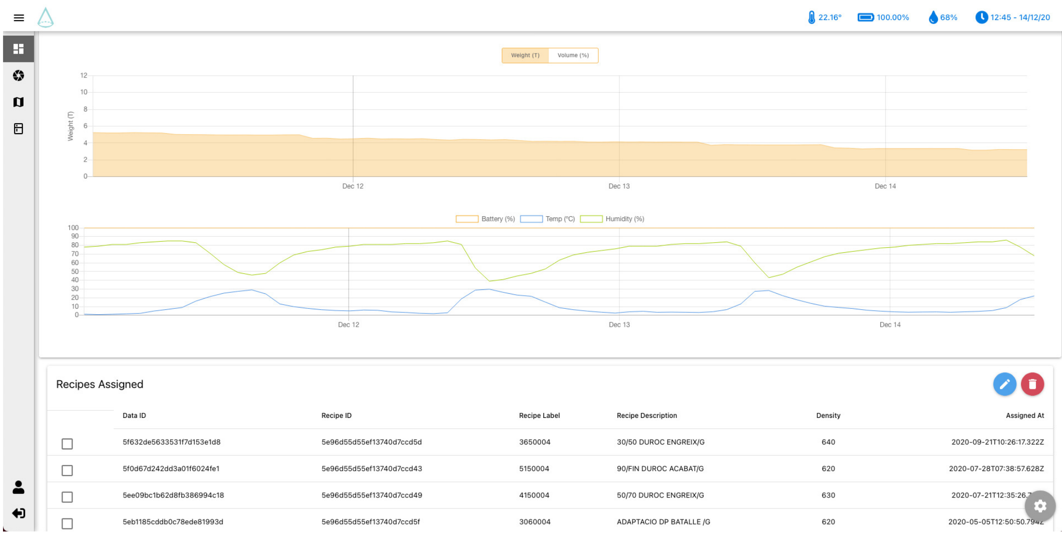



FIGURE D.11: Application: Geometric configuration.

qualified.

- TRL1: 2011 We performed a proof-of-concept in Vall Companys Group (2nd Spanish agrifood corporation with annual turnover of EUR 335M). They self-funded a EUR 350K project aimed to demonstrate the feasibility of a remote feed level monitoring system and a route optimization tool for the feed deliveries. The project was carried out by Ubikwa's founders in 32 farms (with a total of 150 silos) from Lerida (ES). It was a success.
- TRL2/TRL3: In this project, we used commercial ultrasonic devices for level measurement and M2M modems for the communications. The project demonstrated the high impact that a silo remote monitoring system could have over the feed industry, assuring savings of EUR 500 per silo and year (further explain in item 2.1a). Vall Companys expressed the interest in INSYLO, and now is closely following its development. We recently signed a contract with them, who are going to test our solution in 14 silos and, upon its validation, will deploy it in their 10,000 silos.

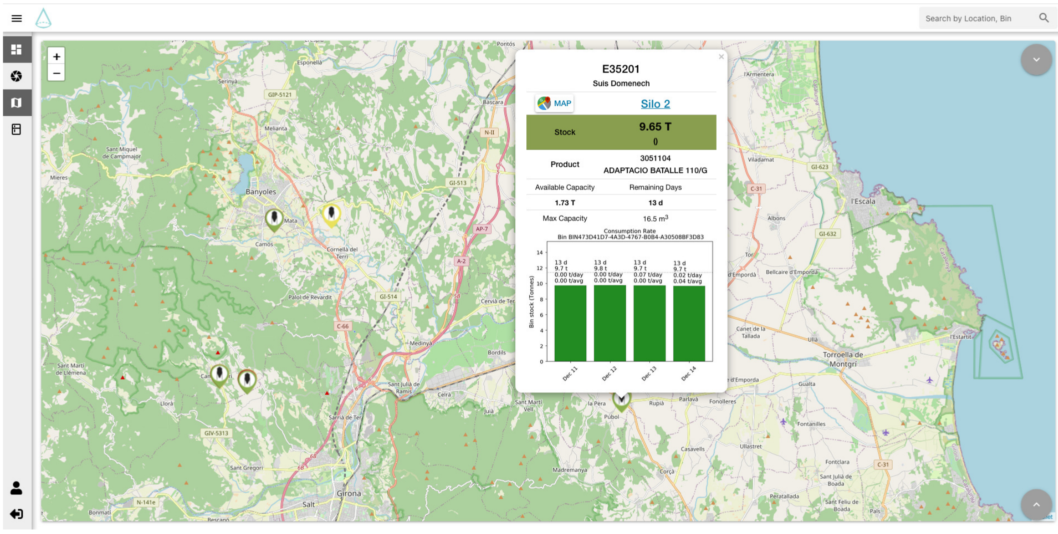



FIGURE D.12: Application map: Bin location and status display.

- TRL4: 2013 Technical advancements: Development of the first version of the innovative 3D volumetric camera that allows us the measuring of the feedstocks in the silos with great accuracy and very low cost.
- TRL5: 2015 Development of INSYLO first working prototype and the cloud platform, with funding support (EUR 100K) received by the Smart Agri-Food Accelerator (SAF) Program Phase I by the European Commission. The device integrates our current 3D Volumetric Camera able to scan the surface of the feed with a depth map of 8x8 points + a solar panel + a module 6LowPan and a module M2M to be wireless connected to Internet.
- TRL6 Feasibility Study: the technical, commercial and financial viability of INSYLO was assessed during Sept.'15-Sept.'16 thanks to the funding support (EUR 140K) received by SAF Phase II. We successfully validated our solution by implementing it, first in two farms from collaborating customers Group Casa Tarradellas (ES) and Horizont Group (DE), and then in two more farms from paying customers Cooperativa Ivars (ES) and Bos Nostrum (ES). We have achieved agreements with more key stakeholders from EU (Annex I).
- TRL7: Since September 2016, guided by the Feasibility Study's conclusions, we have implemented certain technical upgrades (improvement of the measurement's accuracy, implementation of the self-cleaning system + elimination of the stand-alone gateway). We as well continued our commercial action (conversations with our target customers and closing contracts). The funding support obtaining by the Spanish Centre for the Development of Industrial Technology (EUR 212K) in November 2016, and from the Government of Catalonia (EUR 5K) in February 2017 has supported us in the developing of these activities.
- TRL8: With the execution of an Horizont 2020 SME Instrument Phase 2 (2018-2020), under the topic of "Stimulating the innovation potential of SMEs for sustainable and competitive agriculture, forestry, agri-food and bio-based sectors" consisting on a grant of EUR 1M and the IOFEED Project (2019-2020), the current TRL has reached the level 8. INSYLO project is currently at its latest steps towards being commercialised.

# Appendix E

# Environmental Impact

## E.1 Introduction

This document focuses on the plan to obtain the Electromagnetic Component Certifications required to market the solution resulting from the project in:

- the European Union (by obtaining the CE certification),
- the United States (by obtaining the Federal Communications Commission - FCC certification),
- China (by obtaining the China Compulsory Certificate - CCC) and
- Brazil (by obtaining the National Institute of Methodology, Quality and Technology - INMETRO certification).

Before the product gets into the final commercial phase, the company will have to submit the pre-commercial version to the CE certification procedure. This means that before the industrialization, or massive manufacturing of the product, the device must acquire the correspondent certificates to be sold, initially, in Europe and USA. After acquiring a notable presence in these markets, the product will also start the procedure for the remaining markets certifications.

The environmental impact will be measured using the Life Cycle Assessment (LCA) method based on the ISO 14040 and ISO 14044 standards.

This document also describes: 1) the Certification strategy defined for the company taking into consideration each part of the device, 2) What are the requirements of each certification in order the final product can be sold in Europe and USA, 3) The certification procedure.

The aim of this deliverable is to report on the analysis and results of the environmental impact of INSYLO project results.

## E.2 Methodology

Elevation, traffic, and load are variables known for having a direct impact in fuel consumption. A better fuel efficiency is obtained when the vehicle maintains a constant and moderated speed. A study performed by the Environmental Protection Agency shows that acceleration, vehicle weight, and speed limit are the factors that influence on fuel efficiency (Jones, 1980). The performance of a vehicle is better when stops are reduced. In traffic, the vehicle is constantly stopping and accelerating to reach a certain speed. Truckload or extra weight is another important factor in the overall fuel efficiency. In order to report the greenhouse gas emissions associated with an organisation's activities, the carbon emissions need to be converted into "activity data" (ie. distance travelled, litres of fuel used or tonnes of waste disposed). The conversion factor spreadsheets provide the values to be used for such conversions, and step by step guidance on how to use them.

To estimate the $CO_2$ emissions adaptation of tables presented by works like Tansini, Fontaras, Ciuffo, Millo, Rujas, and Zacharof, 2019 for the heavy-duty vehicle (HDV) between 32 and 40 tons for general merchandise are typically utilized. When $CO_2$ estimations are based on these tables, some assumptions are taken with regards the average speed (ie. 80 km/h), the road may be assumed to be flat, and the $CO_2$ emissions produced are considered to be a linear function between what the truck produces when it is fully loaded and the load of the truck $q$ in kilograms, between every node $(i, j)$ traveled as follows:

$$CO_2(q, d)_{ij} = d * (ef_1 - ee_1 Q * q + ee_1) \tag{E.1}$$

$e_1$ when the vehicle is fully loaded referring to weight, constant equal to 189 g/km for an HDV truck, ee; is the $CO_2$ emissions when the vehicle is empty, and it is equal to 93.1 g/km for HDV truck (Elbouzekri, Elhassania, and Alaoui, 2013), and where the constants considered for the model, and $Q$ is the vehicle capacity, so the units are $g * CO_2/km$.

Other strategies rely on the usage of specific software like EcoTransIT World (Demir, Bektaș, and Laporte, 2011), which is the most widely used software worldwide to automate the calculation and analysis of energy consumption and freight emissions. This software relies on a scientifically sound methodology developed by neutral scientific institutes like INFRAS or the Fraunhofer IML. The appendix E elaborates on the carbon footprint estimation for the whole value chain of the thesis proposal, from the sensor development, deployment and the feed service provisioning.

In this work we have applied the LCA method. LCA is a methodology for assessing the environmental impact of a product from "cradle to grave" – meaning through all stages of the product's life from extraction of raw materials through material processing, manufacture, distribution, use, repair and maintenance to disposal or recycling. The procedure of LCA has been standardised as part of the ISO 14000 environmental management standards (ISO 14040 and 14044). According the ISO standards, conducting an LCA involves four main steps:

- Goal and scope definition
- Life cycle inventory (LCI)
- Life cycle impact assessment (LCIA)
- Interpretation

## E.3 Goal and scope definition

The first step of an LCA is the "goal and scope definition". It determines the overall objective of, and the exact questions to be answered by the LCA. During this process, a number of decisions must be taken. Traditionally, the goal and scope definition are done in close cooperation of the commissioning party of the LCA and the practitioner who conducts the LCA. Thereby, the scope and the requirements for the LCA study are determined based on the study's goal. This step is integral for every LCA study, as different goals require different approaches regarding LCA methodology. Apart from the reasons for conducting the study, in this step also information is collected on how the results will be used and who will have access to them. Altogether, the decisions and choices to be made comprise:

- Exact questions to be answered.
- Specific products, product designs or process options to be studied.
- LCA type. In general, a distinction is made between accounting, change-oriented and standalone-type LCA studies. Standalone-type LCA studies usually describe a single product with the objective to gather information on its environmental characteristics. An accounting-type LCA compares different options, but takes a retrospective view, while a change-oriented LCA is also comparative, but has a "looking into the future" component. Thus, change-oriented LCA studies can be applied to assess the environmental impacts of different courses of action.
- Functional unit, a reference flow to which all other flows are related. The functional unit must be quantitative and relate to the studied system. It further enables a comparison between different systems.
- Environmental impact categories. This influences which kind of data has to be collected for the Life Cycle Inventory (LCI). The impact categories should be chosen to reflect, as far as possible, the complete impacts of the inputs and outputs of the studied product system rather than the goal for conducting the LCA study. In (Hawkins, Singh, Majeau-Bettez, and Strømman, 2013), a comparative study on the environmental impacts of conventional and electric vehicles, for example, the impact categories global warming potential, terrestrial acidification, particulate matter formation, photochemical oxidation formation, human toxicity, freshwater eco-toxicity, terrestrial eco-toxicity, freshwater eutrophication, mineral resource depletion and fossil resource depletion were chosen.
- System boundaries in relation to the natural system in space and time, and in relation to technical systems. In setting the system boundaries – deciding which flows to include and exclude for the LCA study – a number of assumptions and limitations, under which the study is conducted, are formed.
- Way how impacts are allocated if processes are linked to more than one product or function. If partitioning is chosen as allocation method, the environmental load is divided between the products or functions while in system expansion the studied system is credited with the environmental load avoided by replacing an equivalent product on the market.

## E.4 Results

In the Life Cycle Inventory (LCI) step, the flows from and to nature for the studied product system or processes are analysed. To conduct the LCI, a flow model of the technical system detailing the input and output flows of the system is constructed based on available data. Apart from raw material input, input of water and energy as well as their release to air, water or land are taken into account. The flow model adheres to the system boundaries set in the goal and scope definition and is restricted to flows relevant to the product system's environmental impact. After data collection, resource use and emissions connected to the investigated system are calculated in relation to the functional unit.

In the Life Cycle Impact Assessment (LCIA) step, the significance of potential environmental impacts is evaluated based on the LCI flow result. This step in an LCA consists mainly of three parts:

- Classification (assignment of inventory parameters to impact categories)
- Characterisation (calculation of relative contribution of emissions and resource consumption to the different categories of environmental impact)
- Weighting

### E.4.1 Interpretation

The interpretation chapter summarises the results from the inventory analysis and impact assessment. The outcome of the interpretation step is usually a set of conclusions and recommendations. In a standard LCA, this step includes: a) Identification of significant issues based on the results of the LCI and LCIA, b) Evaluation of the study (completeness and consistency check) and c) Conclusions, recommendations and reporting.

### E.4.2 LCA's objectives and goal

The goal and scope of the LCA presented here was specified by two questions to which the study should provide an answer. First, what is the environmental impact of producing INSYLO technologies and devices in term of Carbon footprint? and second, what is the environmental impact that is avoided by using INSYLO in the feed-stock value chain? The evaluation of the environmental impact and the carbon foot print generated by the INSYLO technologies will be evaluated in a basic mode presenting the impact of product manufacturing and the impact of using the product in the value chain and the impact of the benefits it produces. The LCA will be evaluated without using any of the software tools designed following the ISO standards. The consolidated set of inventory parameters is assessed according to data quality criteria based on requirements according to ISO 14040/14044 series.

### E.4.3 Life cycle inventory

For responding to the first question specified in the goal and scope definition, a standalone LCI and LCIA for a INSYLO device with the compounds detailed below has been performed, which covers the extraction of raw materials and production of the device including all the components composing the: battery pack, casing, data management system, internal cabling, metal structure, communications system, its installation and the recycling of the device. The impact and cost of the use of DDBB and the AWS services are really residual due to the low volume of the project deployment (of hundreds of devices), but will be permanently analysed when the deployment volume, as well as the volume of processed data, increases. Thus, six different life cycle phases have been distinguished:

1. Materials used to build all components.
2. Processing of materials and components used.
3. Installation of the device on the top of the silos.
4. Use phase of the INSYLO sensor.
5. Recycling, final disposal of materials and components used.

### E.4.4 Production of the hardware components used

For estimating the environmental impact of phases (1), (2) and (5) above, a survey of LCA studies of different electric products has been made. For each of the following components, an analysis has been assessed:

- Data controller Printed Circuit Board (PCB). Self-developed control board to manage all the systems, acquire data, process it and send it to the cloud using a communications interface.
- Structured light camera. Off-the-shelf structured light camera.
- Raspberry processor and communications board with a 65mm x 30mm form factor.
- Composite plastic casing (for camera and main body).

- Solar panel. 156mm x 156mm multi-silicon solar panel to transform solar light into energy to recharge the battery.
- Battery. A rechargeable lithium-ion 5V battery as power supply.
- Metal (iron) plates and pieces. Few little extra pieces for the adaptation and sealing of the device to the Silo surface.

| COMPONENT | Units | IMPACT per Unit | TOTAL |
|---|---|---|---|
| PCB | 350 sqrcm | 243 Kg CO2/sqrm | 8.5 |
| ORBBEC | 1 | 8 Kg CO2/U | 8 |
| RaspBerry Pi | 1 | 15 Kg CO2/U | 15 |
| Casings | 585 gr. | 3.6 Kg CO2/Kg | 2.16 |
| Solar Panel | 24.336 sqrmm | 116 Kg CO2/sqrm | 2.82 |
| Battery | 0.104 Kg | 14 Kg CO2/Kg | 1.456 |
| Metal elements | 275 gr. | 0.464 Kg CO2/Kg | 0.1276 |
| TOTAL | | | 38.06 Kg CO2 |

TABLE E.1: Manufacturing environmental impact in terms of $CO_2$ generation per device.

Then, the approximate impact for the manufacturing process of the INSYLO product is of 38.06 Kg of $CO_2$ per device (Table E.1). This amount can be compared to DEFRA's Conversion Factors say office machinery including computers, in 2009, worked out at 0.53 kg CO2e per pound spent.

### E.4.5 Use phase of INSYLO

During the usage of INYSLO (phase 3 above), and regarding the impact on the carbon footprint will take into consideration the LCA Env impact reference for the whole life-cycle of a single device including:

#### INSYLO installation

The device installation main impact in the carbon footprint is directly related to personnel transports cost (air or on road), and the shipping of the device. It is considered that a mean installation process will require a displacement of 60 miles per 1.5 devices (mean number of silos per farm). Here we can add a 10% ratio travel distance for maintenance for each device installed during the life-cycle.

#### INSYLO energy consumption

The consumption of the device is almost null, as it produces its own energy thanks to the use of Solar Panels to recharge its batteries.

#### Indirect Carbon Footprint due to transfer of data

According to the American Council for an Energy-Efficient Economy: 3.1 kWh of electricity / GB of transferred data. And 0.233 Kg CO2 / kWh, this means: 0.7223 Kg CO2 / GB of data transferred. During the full lifecycle of a single device (5 years) it is estimated that it would transfer a total of 1,345GB of data (Results shown in Table E.3, based on 22MB of data transfer monthly considering also OTAs and LOGs information files – aprox. 3MB to add).

| COMPONENT | Units | IMPACT per Unit | TOTAL |
|---|---|---|---|
| Installation & Maint. | 44 miles | 0.404 Kg CO2/mile | 17.77 |
| Energy Consumption | – | – Kg CO2/KWh | – |
| Data Transfer | 1,345 GB | 0.7223 Kg CO2/GB | 0.97 |
| TOTAL | | | 18.74 Kg CO2 |

Table E.2: Carbon footprint for Usage of INSYLO device.

### E.4.6 Product recycling

At the end of INSYLO product life-cycle the final phase – Phase 5 – is the recycling (or EOL) of INYSLO devices and each one of its parts. This includes transport to recycling plant and energy demand at the plant. Recycling credits are not applied at this stage, to avoid double counting (the manufacturing process assumes a market mix of virgin and recycled materials).

For the calculus if the environmental impact of this final phase, we have to detail that the impact of the off-the-shelf products or parts used in device's manufacturing, and taking as correct the impact assessment and figures provided by each part manufacturer, the total amount or contribution of each part has been considered to include the recycling of each part (mainly the 3D camera, the mainboard, the solar panel, etc.).

It is considered that the contribution to carbon footprint of an IT device is almost the 4-5% of its total impact.

### E.4.7 Interpretation

Table E.1 summarize the environmental impact for the manufacturing of each INSYLO device taking into consideration the components of the device. Some components are complex elements – like the mainboard, or the 3D camera used for data acquisition – and the impact of these parts have been achieved consulting each part manufacturer. Once the company receives all the components or parts, they have to be integrated and programmed. This procedure has not been included into the carbon footprint measure. Table E.3 summarize the impact of INSYLO installation considering a medium to massive deployment of devices (installing a mean of 200 to 250 devices per month), and using data agreed with a local installer near the location of the farms and local or short-range travel.

The total amount for the Carbon Footprint of manufacturing, device installation, and device usage is of:

| | |
|---|---|
| INSYLO Device Impact | 56,81 Kg $CO_2e$ |

Table E.3: Total impact of the INSYLO device.

If the environmental impact of the production and logistics (installation) of the INSYLO device is accounted entirely to the 1st life. The other environmental impacts are marginal (data usage - less than 5% - and null net energy consumption). These findings are in

| TRANSPORT TYPE | LCA EMISSIONS |
|---|---|
| Trailer truck with a GCW of 35 tonnes | 189 g $CO_2$ / t.km |
| Straight truck with a GVW of 19 tonnes | 332 g $CO_2$ / t.km |
| Semi-trailer truck with a GCW of 40 tonnes Large volumes | 93,1 g $CO_2$ / t.km |

TABLE E.4

| COMPANY | TRUCK | DISTANCE | TOTAL |
|---|---|---|---|
| BATALLÉ | 19Tn | 181,977Km | 60.42 tones $CO_2$ |
| | 35Tn | 207,504Km | 19.31 tones $CO_2$ |
| TOTAL | | | 79.84 tones $CO_2$ |

TABLE E.5

line with assessments of the environmental impact of different IoT devices, as well as in LCA studies on remote sensors used in the industrial sector. The standards for the LCA emissions for logistics and transport usage, given the type of truck and the capacity of the vehicles used by this project feed suppliers is:

Using the data obtained from Batallé (in Spain), we can calculate the actual environmental impact of each company in reduction:

This scenario has been chosen because it shows the most relevant effect of large-scale deployment of INSYLO in the feed supplier: avoiding generation 2% of the measure footprint and consequently avoiding back-up operation or urgent orders and related environmental impact (According the experiments done with Batalle's logistics).

### E.4.8 Carbon foot print

Practically all projects that arise from the need to measure the HC of a product or system, not only have the objective of calculating GHG emissions, but also have to establish measures to reduce or offset said emissions. The most common is to carry out this calculation through a methodology known as Input-Output Analysis (AIO). The AIO was developed in the 1930s with the aim of providing empirical support for the study of the relationships between the different components (economic activities) of an economy, based on the general equilibrium theory (Leontief, 1936). This analysis is based on the use of Input-Output Tables, which is a set of equations that describes the flow of goods and services between the different sectors of an economy in a given period. In this way, thanks to the AIO, we can link the final demand for goods and services with the direct and indirect emissions associated with its production, regardless of the country where it is located. Through this, it is possible to quantify to what extent a certain economic activity demands inputs from other economic activities in its production process and, consequently, to what extent an increase in the final demand for a good or service implies an indirect demand for others. goods and services used as intermediate inputs in the production of said product.

## E.5 Conclusions

The GHG emissions were calculated according to ISO 14040 and ISO 14044, the two international standards governing the investigation and evaluation of the environmental impacts of a given product over their life cycle. The impact of the INSYLO whole life-cycle has been detailed taking into consideration product manufacturing, product installation, and potential maintenance and EOL. Also, once the device is deployed, the usage of the device is taken into consideration.

We can compare the usage of the INSYLO device to the usage of an HDD device or a very small PC, but improving the energy usage at INSYLO is using solar panels to recharge its batteries and have an intelligent algorithm to optimise use of energy in case of low solar radiation.

A must for the IoT devices is to evolve to a more optimised configuration, due to the improvement and upgrade of each part that compounds the devices, and the use of lower carbon footprint compounds and materials due to the reduction of scale manufacturing.

The option to obtain ISO:14040 and ISO:14044 quality standards will be explored as the project evolves.

# Appendix F

# Family, Friends and Fools

Apart from the Conference, Workshop and the daily routine, this project has performed intense activities and operations on field. Here is showcased some pictures from these activities with family, friends and fools during the thesis period.

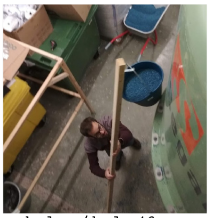

deploys/deploy13.png

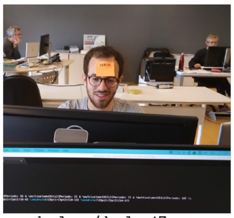

deploys/deploy15.png


deploys/deploy10.png


deploys/ff1.jpg


deploys/deploy12.png

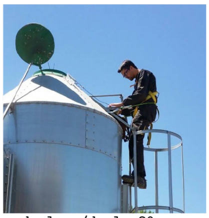

deploys/deploy16.png


deploys/deploy17.png


deploys/deploy18.png


deploys/deploy19.png


deploys/deploy2.png


deploys/deploy20.png


deploys/ff3.jpg


deploys/deploy22.png

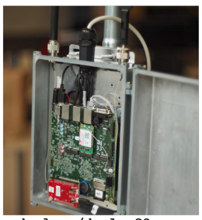

deploys/deploy24.png


deploys/deploy25.png


deploys/deploy26.png


deploys/deploy27.png


deploys/deploy28.png


deploys/deploy29.png


deploys/deploy3.png


deploys/deploy30.png


deploys/deploy31.png


deploys/deploy32.png


deploys/deploy33.png


deploys/deploy34.png


deploys/deploy35.png


deploys/deploy36.png


deploys/ff2.jpg


deploys/deploy39.png


deploys/deploy40.png


deploys/deploy4.png


deploys/deploy5.png


deploys/deploy6.png


deploys/deploy7.png


deploys/deploy8.png


deploys/deploy9.png

INSYLO has taken an international direction since the beginning. The collaboration with external partners from multiple countries where we have done pilots has been enriching and also a pleasure. We have enjoyed the English weather as well as the Arab hospitality while we were on field, drilling silos and dealing with cows, pigs, chickens and farmers.

During these years I have had the opportunity to enjoy conferences and the work journey with some members of the ICSO Team (Figure F.1).

And of course, I also felt the pain and the glory with INSYLO's members (Figure F.2).


FIGURE F.1: UOC Collaborators at WSC'19.

FIGURE F.2: INSYLO Team at fun-champion activity.

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